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Success Factors Impacting Artificial Intelligence Adoption --- Perspective From the Telecom Industry in China

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SUCCESS FACTORS IMPACTING ARTIFICIAL INTELLIGENCE ADOPTION---

PERSPECTIVE FROM THE TELECOM INDUSTRY IN CHINA

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ABSTRACT

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As the core driving force of the new round of informatization development and the industrial revolution, the disruptive achievements of artificial intelligence (AI) are rapidly and comprehensively infiltrating into various fields of human activities. Although technologies and applications of AI have been widely studied, and factors that affect AI adoption are identified in existing literature, the impact of success factors on AI adoption remains unknown. Accordingly, the main study of this paper proposes a framework to explore the effects of success factors on AI adoption by integrating the technology, organization, and environment (TOE) framework and diffusion of innovation (DOI) theory. Particularly, this framework consists of factors regarding the external environment, organizational capabilities, and innovation attributes of AI. The framework is empirically tested with data collected by surveying telecom companies in China. Structural equation modeling is applied to analyze the data. The results indicate that compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership are significantly related to AI adoption. Managerial capability impacts other organizational capabilities and innovation attributes of AI, but it is indirectly related to AI adoption. Market uncertainty and competitive pressure are not significantly related to AI adoption, but all the external environment factors positively influence managerial capability. The study provides support for firms' decision-making and resource allocation regarding AI adoption. In addition,

based on the resource-based view (RBV), this article conducts study 2 which explores the factors that influence the firm sustainable growth. Multiple regression model is applied to empirically test the hypotheses with longitudinal time-series panel data from telecom companies in China. The results indicate that at the firm level, the customer value and operational expenses are significantly related to sustainable growth. Also, at the industry level, industry investment significant impacts sustainable growth. Study 2 provides insights for practitioners the way to keep sustainable growth.

This dissertation is dedicated to my parents and family for their unconditional love, unwavering support, and encouragement that enabled me to pursue and complete it. This dissertation is also dedicated to the help of faculty, staff, and my classmates in Strome College of business. Without your endless support and belief in my abilities, I would not have completed this dissertation.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
3G/4G	The /4th Generation of mobile network
5G	The 5th Generation of mobile network
AI	Artificial Intelligence
AIC	Akaike's Information Criterion
AIIA	Artificial Intelligence Industry Development Alliance
AIS	Association for Information Systems
AMOS	Analysis of Moment Structures
AMT	Advanced Manufacturing Technology
APIs	Application Programming Interfaces
ARPU	Average Revenue Per User
AVE	Average Variance Extracted
CAICT	China Academy Information and Communications Technology
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CRM	Customer Relationship Management
DEC	Digital Equipment Corporation
DF	Degrees of Freedom
DOI	Diffusion of Innovation
EDI	Electronic Data Interchange
EM	Expectation Maximization
ENI	Experiential Networked Intelligence
ETSI	European Telecommunications Standards Institute
GGF	Government Guidance Fund
HOG	Histograms of Oriented Gradients
IFAI	International Federation of Artificial Intelligence
IoT	Internet of Things
IPO	Initial Public Offering
IS	Information System

IT	Information Technology
KMS	Knowledge Management Systems
MIIT	Ministry of Industry and Information Technology
ML	Machine Learning
NLP	Natural Language Processing
NPD	New Product Development
QFD	Quality Function Deployment
RAN	Radio Access Networks
RBV	Resource-based view
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SGR	Sustainable Growth Rate
TAM	Technology Acceptance Model
TOE	Technology, Organization, and Environment
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
XCON	eXpert CONfigurer

1. INTRODUCTION

The concept of Artificial Intelligence (AI) was first proposed in 1956 in the Dartmouth Conference hosted in the U.S.(Crevier,1993). Then AI lingered in people's minds and slowly hatched in research laboratories. Since 2000, particularly after 2015, the rapid development of intelligent hardware (sensors and chips), the evolution of algorithms, and the support of big data have constantly driven the development of AI. In the flourishing period, many applications of AI become available. So far, AI has been integrated into many aspects of society. Applications of AI have been widely adopted by many firms in diverse industries across the world. Applications of AI include advanced robotics, autonomous vehicles, the specific regions of medical diagnostics, and intelligent computers (Schmidhuber, 2007; Xu, Xu, & Li, 2018). At present, AI can write complex codes, predict choices, interact with the human in real time, mine trillions of data, and provide solutions. AI technologies, such as natural language processing, machine learning, and deep learning, bring sophisticated data analysis capabilities to existing applications across a wide range of industries and greatly facilitate firms' management, planning, and operation (Kasemsap, 2017). Therefore, firms adopt AI to improve their decision making, ecosystems, and re-creation of the customer experience (Alsheibani, Cheung, & Messom, 2018). AI is wielding a profound impact on the global economy, social progress, and people's daily life.

Considered as one of the main enabling technologies and general technologies of the fourth industrial revolution, AI has received great attention from various industries. Among the industries that adopt AI, the telecom industry benefits a lot from leveraging AI technologies. In the past two decades, the telecom industry has been driven by the technology revolution and digital transformation. Telecom operators not only work on network infrastructure and data pipelines but

also provide AI computing capabilities and massive data. To cope with the dramatic changes and fierce competition, telecom operators are experiencing major transformation. They aim to catch up with the technology leaders, such as Google, Amazon, or Microsoft, in the transition to the 5th generation of mobile network (5G). AI makes it possible for telecom operators to achieve their goals. With the help of comprehensive network infrastructure and full-service network capabilities, on the one hand, operators can enrich telecom services, expand business capabilities, and improve operational efficiency and service via AI technologies. On the other hand, operators can expand service capabilities and channels for vertical industries by providing generic telco AI platforms. This is an important opportunity to help operators realize the digital transformation of integrated information services. The advent of 5G technologies in mobile networks will boost AI in the telecom industry (Li, Xu, & Zhao, 2018). At present, AI technologies are carried out within the world's major telecom operators and have generated many positive effects. AT&T, SK Telecom (Korea), and NTT DoCoMo (Japan) have connected AI with their strategies. AI has been recognized as a strategic information technology innovation tool to improve telecom operators' competitiveness (Neokosmidis, Rokkas, Xydias, Albanese, Siddiqui, Colman-Meixner, & Simeonidou, 2018). Some telecom operators begin to promote the application of AI technologies for improving their network performance, enhancing customer experience, and mining more business opportunities. According to Tractica (2018), telecom operators are expected to use AI mainly for monitoring network operation from 2016 to 2025, and their investment in AI account for 61% of the entire expenditure on AI by all industries. Currently, although some initiatives of AI have been adopted in leading telecom operators, such as the virtual assistants to support customer service and marketing, the intelligent customer relationship management (CRM) systems, and the network operation monitoring and maintaining (Tractica, 2018), many applications of AI

are still at their conceptual stage and have not generated any commercial value, particularly those applications regarding network management and predictive maintenance. As a result, AI applications are facing challenges. Therefore, a deep understanding of the success factors of AI adoption will provide implications for associate academics, potential AI adopters, the government, and AI vendors.

Existing literature has identified the success factors for IT adoption (Oliveira & Martins, 2011) and has examined the process of how companies adopt IT innovations. Previous studies on AI mainly focus on techniques and applications (Qi, Wu, Li, & Shu, 2007; Walczak, 2018). However, organizational or managerial issues regarding AI, particularly, the success factors that affect AI adoption are overlooked. Studies that empirically validate the direct and indirect effects of the AI characteristics as well as the impact of the underlying technology, organization, and environment contexts are not available. Accordingly, this study aims to answer the following questions: (1) What factors are concerned by firms when they plan to adopt AI technologies? (2) How do these factors interrelate to influence AI adoption? (3) Do these factors affect AI adoption at the same level? In specific, this study proposes a framework to explore the impacts of success factors on AI adoption by integrating the integrates technology, organization, and environment (TOE) framework (Tornatzky & Fleischer, 1990) and diffusion of innovation (DOI) theory (Rogers, 1995). Particularly, this framework consists of factors regarding the external environment, organizational capabilities, and innovation attributes of AI. Ten success factors related to AI adoption are identified through the literature review on studies published in the areas of innovation, diffusion, implementation, and adoption of information technology. The framework is empirically tested with data collected by surveying telecom companies in China. Structural equation modeling is applied to analyze the data. The results indicate that compatibility, relative advantage,

complexity, managerial support, government involvement, and vendor partnership are significantly related to AI adoption. Managerial capability impacts other organizational capabilities and innovation attributes of AI, but it is indirectly related to AI adoption. External environment factors, including market uncertainty, and competitive pressure, are not significantly related to AI adoption, but in the additional study, government involvement, market uncertainty, and competitive pressure are found to influence managerial capability significantly. This study contributes to the wider body of scientific knowledge about AI adoption that has so far not studied. It provides support for firms' decision-making and resource allocation regarding AI adoption. It also provides insights for academia, potential AI adopters, governments, and AI vendors. In addition, study 2 was conducted to explore the key factors affecting firm sustainability using longitudinal time-series panel data. Multiple regression model is used to test the hypotheses. Study 2 finds that at the firm level, the customer value is positively associated with firm sustainable growth, and the operational expense negatively influences firm sustainable growth. Moreover, at the industry level, industry assets investment significant impacts on firm sustainable growth. The findings provide empirical evidence for factors that may affect a company's sustainable growth. It also provides insights for practitioners the way to keep sustainable growth.

The remainder of the study includes a thorough examination and analysis of the literature, methodology, results, and a discussion of recommendations for researchers and practitioners. Firstly, it reviews the literature related to AI and describes AI applications as well as the theoretical foundations for AI adoption. Secondly, a research model and an updated model for investigating the factors that influence AI adoption are proposed, followed by the research method, data analysis, and results. Thirdly, study 2 about firm sustainable growth research is carried out, including

proposed hypotheses, data analysis, and results. Then the discussion of the research findings and implications for associated academics and practitioners are provided before the conclusion.

2. LITERATURE REVIEW

2.1 Artificial Intelligence (AI)

2.1.1 Definition and development of AI

With the revolution of computing technology in the early 20th century, AI and initial AI theory emerged in the middle 20th century (Meek, Barham, Beltaif, Kaadoor, & Akhter, 2016). In 1956, John McCarthy first coined the term artificial intelligence (AI) at the Dartmouth Conference in the U.S. (Crevier,1993). At that time, AI was thought of as the process in which a computer was applied to construct a complex machine with the same essential characteristics as human intelligence. Later, the definition of AI evolved. For example, Shenoy (1985) defines AI as an obscure branch of computer science. Rich and Knight (1991) note that AI is demonstrated by machines and they think that different from the natural intelligence displayed by humans and other animals, AI is how to make computers do things intelligently like humans. Nilsson (2014) points out that AI is a subpart of computer science that involves how to provide intelligent complexity to computers. Kasemsap (2017) thinks that AI is a branch of science that helps machines find the right solution for solving complex problems in a human-like way. Pannu (2015) argues that AI is neither psychology nor computer science because it emphasizes computation, perception, reasoning, and action. He points out that AI has advantages over natural intelligence because it is more permanent, more consistent, cheaper, easier to copy and spread, and can record and perform certain tasks faster and better than humans. Although scholars define AI from diverse perspectives, they agree that AI involves computer science, information engineering, mathematics, psychology, linguistics, and philosophy. So far, AI does better than humans in playing chess. However, humans still do better in understanding pictures and learning (BBC News, 2016; Pannu, 2015).

AI emerged as an academic field in 1956 when its name and mission was defined. The main goal of AI is to enable machines to perform complex tasks that typically require human intelligence. Early research on AI was heavily influenced by philosophy, logic theory, and fiction (Buchanan, 2005). Later, the domains of AI changed to application, effects, and uses. According to CAICT and Gartner (2018), the development of AI experiences three stages, as shown in Figure 1: infancy (1956-1980), industrialization (1980-2000), and flourishing (2000-2018).

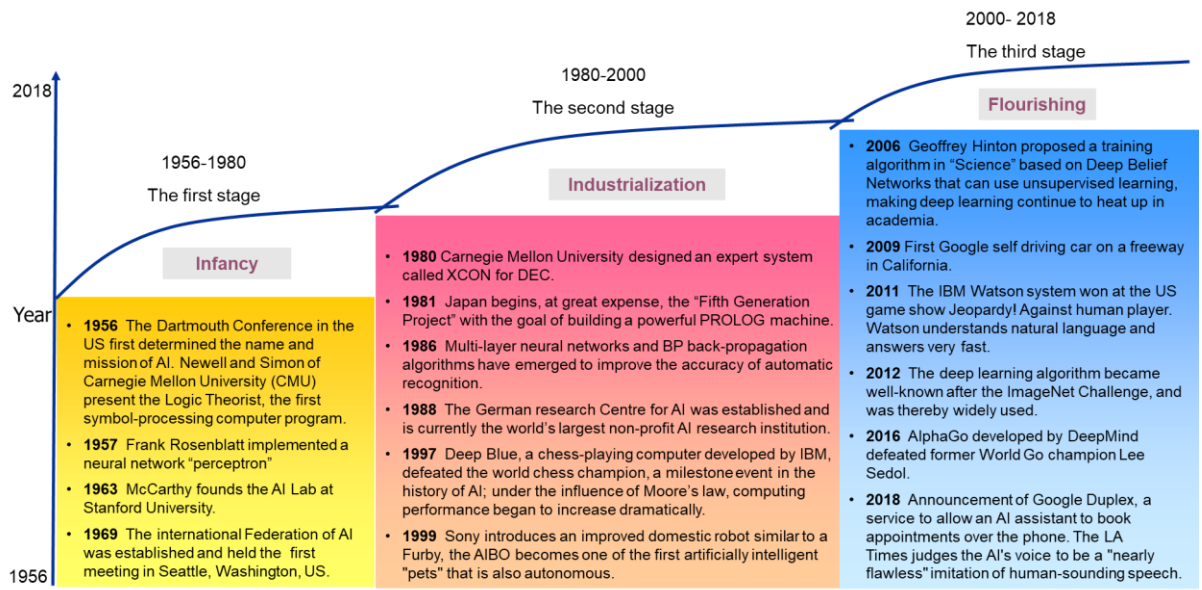

Figure 1. AI Development Milestones (CAICT & Gartner, 2018)

Studies on AI began in the first stage. For example, McCarthy (1960) discusses the function of AI. In 1969, the International Federation of Artificial Intelligence (IFAI) was founded and its first meeting was hosted in Seattle, Washington. Although AI is still in its infancy era at this stage, the number of AI research and applications grow continuously. Moreover, the understanding and awareness of AI became more comprehensive and specific.

In the second stage, AI stepped into industrialization in several developed countries. In 1980, Carnegie Mellon University designed XCON (eXpert CONfigurer) for Digital Equipment Corporation (DEC), the second-largest computer manufacturer in the U.S. at that time. After XCON came into production, it saved enterprises $40 million each year (Prendergast & Winston, 1984). From 1985, IBM spent 12 years on building Deep Blue, a chess-playing supercomputer that was considered to have domain-specific AI. Deep Blue beat the reigning world chess champion, Garry Kasparov, on May 11, 1997. This is a milestone in the development of AI (McCorduck, 2009). However, the development of AI did not occur in the U.S. only. In 1982, Japan invested $850 million to develop AI computers with the goal of building a powerful PROLOG machine (Shapiro,1983). In 1988, Germany established a research center for AI, the largest non-profit AI research institution in the world at the time.

In the third stage, the rapid development hardware, particularly sensors and chips, along with the support of big data drives the flourish of AI. A variety of products use AI technologies, such as advanced robotics, autonomous vehicles, and intelligent computers (Schmidhuber, 2007). According to Clark (2015), the number of software projects using AI in Google rise dramatically between 2012 and 2015. In 2016, AlphaGo, developed by DeepMind, defeated former world Go champion Lee Sedol (BBC News, 2016). In the Go of Go Summit of 2017, AlphaGo won three games with Ke Jie, who was the top one in the world for two consecutive years (METZ, 2017). AlphaGo's achievement marks a significant milestone in the development of AI because compared with chess, Go is a more complex game. Due to the improvement in computing infrastructure, specific Al algorithms can perform better than human experts today.

2.1.2 Technologies and applications of AI

Although various AI technologies have been ready for decades, it is the increased network and data processing speed and advances in hardware that make commercial applications of AI available. In the 21st century, the development of computer capabilities, large amounts of data, and theoretical understanding drive the flourish of AI technologies. Major advances are achieved in converting the research and technology of AI into performant products.

2.1.2.1 Machine vision

Machine vision, also known as computer vision, refers to the use of cameras and computers to replace human eyes' recognition, tracking, and measurement of objects, and further to do image processing. This makes computer processing more suitable for human eye observation or sending images to the instrument (Chen, 2016). Computer vision technology is one of the important core technologies of AI. Compared with traditional visual technologies, machine vision enables computers to have a visual perception like human grading recognition of image features with high speed, high precision, and high accuracy. Its biggest feature is fast speed, a large amount of information, and many functions. It has been widely adopted in video surveillance, autonomous driving, vehicle/face recognition, medical image analysis, archeology, and aerial remote sensing measurement (Barcelo & De Almeida, 2012).

2.1.2.2 Expert System

The expert system can be considered as one of the first genuinely successful applications of AI and one of the fastest growing and most widely used technical directions in the field of AI (Russell & Norvig, 2016). It includes a well-organized body of knowledge that mimics expert problem-solving skills in a limited area of expertise with three components, namely the knowledge base,

the inference engine, and the user interface (Bahrammirzaee, 2010; McDermott, 1982; Pannu, 2015). XCON is the first successful expert system that was developed to verify the technical correctness of customer orders and to guide the assembly of such orders for the DEC. An expert system has a huge impact on various fields. Usually, the expert system is the first step adopted by many firms towards AI (Muller, Magill, Prosser, & Smith,1993; Rao, Nahm, Shi, Deng, & Syamil, 1999). However, after the hype in the 1980s, the expert system was no longer a separate AI concept in the 1990s. However, it has still been applied to solve complex tasks. For example, an expert system has been widely used in the process of decision support and problem-solving (Liao, 2005). The expert system is not just rigorous mathematical or simulation schemes. It can handle facts or heuristics as well as coping with uncertain, unreliable, or even missing data (Jayaraman & Srivastava, 1996; Waterman, 1986).

2.1.2.3 Natural language understanding

Natural language understanding includes natural language processing (NLP), speech recognition, and speech synthesis (Qi et al., 2007). Voice-based search queries are currently the fastest growing search type. With the help of AI, computers can be programmed for gaining knowledge, understanding language, and translating languages (Norvig, 2012). In specific, NLP can let computers understand the thoughts or intentions of natural language texts and express these thoughts or intentions in natural language texts as well. Therefore, NLP works well for text analytics because it facilitates understanding sentence structure and meaning, sentiment, and intent through statistical and machine learning methods. Currently, NLP has been applied in fraud detection and security, automated assistants, machine translation, subtitle generation, text semantic comparison, and unstructured data mining (Hauptmann, Witbrock, & Christel, 1997). There are already some commercially available NLP products on the market, such as IBM's Watson, Apple's

Siri, Amazon's Alexa. Furthermore, AI algorithms can understand human language and take action in response. Speech recognition refers to the transcription and transformation of human speech into format useful text or command for computer applications. Speech synthesis means that a computer generates human-like speech by reading the corresponding text or commands. They are currently used in interactive voice response systems, voice assistant, and mobile applications (Kasemsap, 2017).

2.1.2.4 Machine learning and deep learning

Machine learning is the most powerful tool offered by Al. It refers to designing, training, and deploying models to applications, processes, and other machines by providing algorithms, Application programming interfaces (APIs), development and training toolkits, data, as well as computing power (Feng & Xu, 2000; Kasemsap, 2017). The most prominent success of Al stems from advancements in machine learning algorithms. The goal of machine learning is to use algorithms for parsing and learning from data, and then making decisions and predictions about events in the real world (Chen, Chen, Gorkhali, Lu, Ma, & Li, 2016). Thus, machine learning uses many data to train and learn how to accomplish tasks. Algorithms adopted in machine learning include decision trees, clustering, Bayesian classification, support vector machines, expectation maximization (EM), and adaptive boosting (Adaboost) (Goldberg & Holland, 1988). The main applications of machine learning are fingerprint recognition, Haar-based face detection, and histograms of oriented gradients (HoG)-based object detection (Li, Cheng, Guo & Qiu, 2018).

Deep learning, also known as deep neural network, is a technology for implementing machine learning. As a special type of machine learning, deep learning enables computers to learn from experience and understand the world based on the hierarchy of concepts (Goodfellow, Bengio, Courville, & Bengio, 2016； Li et al., 2018). Deep learning consists of artificial neural networks

(ANNs) with multiple abstraction layers. It can discover complex structures in large data sets and indicate how the machine should change its internal parameters by applying backpropagation algorithms (LeCun, Bengio & Hinton, 2015). Particularly, deep learning is good at identifying unstructured data, such as images, sounds, videos, and texts. It can be used in almost all popular AI applications. As data grows complex, deep learning will be a keyway to understand all possible and relevant data and provide the most intelligent insights. Currently, deep learning is primarily used in pattern recognition and classification applications supported by large data sets (Kasemsap, 2017; Xu, He, & Li, 2014). By using deep learning techniques along with reinforcement learning, AlphaGo beat the best human players.

2.1.2.5 AI applications in industry

The rapid development of AI is profoundly changing the world. Many countries and organizations have developed strategic plans to seize the opportunities generated by AI (CAICT & Gartner, 2018). For example, the U.S. National Science and Technology Council & Networking and Information Technology Research and Development Subcommittee issued *the National Artificial Intelligence Research and Development Strategic Plan* in 2016 (NITRD, 2016). The U.S. Information Technology Industry Council released *Artificial Intelligence Policy Principles* in 2017 (ITI, 2017; Dutton, 2018). US President Trump signs executive order *American AI Initiative* in February 2019, which formulated the AI development direction in the future from investment, open government data resource capabilities, related standards construction, employment crisis response, and the formulation of relevant international standards. The Chinese State Council issued *A Next Generation Artificial Intelligence Development Plan* in 2017 (Creemers, 2017; Dutton, 2018). In the same year, the Ministry of Industry and Information Technology in China released *the Three-Year Action Plan for Promoting Development of a New Generation Artificial*

Intelligence Industry (2018-2020) (Beckett & Ge, 2017; Dutton, 2018). The Japanese government issued *Artificial Intelligence Technology* in 2017 (Dutton, 2018). U.K. government established *the Growing the Artificial Intelligence Industry in the U.K.* in 2017(Hall & Pesenti, 2017). European Union released the *Human Brain Project* in 2013 (Markram, 2012). Institute Electrical and Electronics Engineers issued the *Ethically Aligned Design, Version 2* in 2017(IEEE, 2017). These regulations and policies build a favorable environment for the development of AI.

At present, the main AI applications are related to big data, visual service, NLP, and intelligent robot. Most AI applications are applied in business, finance, healthcare, and automobile (CAICT & Gartner, 2018). Intelligent healthcare includes medical imaging, clinical decision support, speech recognition, drug discovery, health management, pathology, and so on (Zang, Zhang, Di & Zhu, 2015). AI provides potential applications for intelligent healthcare. For example, machine learning can predict drug performance, gene sequencing, and crystal form. Natural language understanding enables electronic health records, intelligent queries, and guidance. Machine vision can realize medical image recognition, lesion identification, and skin disease self-test (CAICT & Gartner, 2018). By improving the efficiency of medical institutions and personnel and reducing medical costs (Hamet & Tremblay, 2017), AI can enhance people's health (Fast & Horvitz, 2017).

In addition, big data-based AI technologies can drive the upgrade of financial technology. AI can rebuild the ecological structure of the current financial industry, making financial services (banking, insurance, wealth management, loans, and investment) more humane and intelligent (CAICT & Gartner, 2018). So far, artificial neural networks, expert system, and hybrid intelligence systems have been widely applied in financial services. Applications include credit evaluation, portfolio management, and financial prediction and planning (Bahrammirzaee, 2010; Chen, 2017; Fethi & Pasiouras, 2010).

Moreover, AI enables robots to have a human-like perception, coordination, decision-making and feedback capabilities. Intelligent robots can be categorized into intelligent industrial robots, intelligent service robots, and intelligent specialize robots (CAICT & Gartner, 2018). Intelligent industrial robots can perform packaging, positioning, sorting, assembly, and detection. Intelligent service robots can provide family companion, business service, healthcare, retail sales, and rehabilitation of disabled people. Intelligent specialize robots can conduct reconnaissance, search and rescue, as well as firefighting (Alsamhi, Ma, & Ansari, 2018; Nolfi, Bongard, Husbands, & Floreano, 2016; Siciliano & Khatib, 2016).

Other than healthcare, finance, and robots, AI has been applied in retail (Semenov, Chernokulsky, & Razmochaeva, 2017; Syam & Sharma, 2018), education (Timms, 2016; Zhou & Lawless, 2015), smart home (Xu, Wang, Wei, Song, & Mao, 2016), agriculture (Smith, 2018; Xu, Liang, & Gao, 2008), manufacturing (Bi, Xu, & Wang, 2014; Kusiak, 2017; Li, 2017), and intelligent driving (Basarke, Berger, & Rumpe, 2007; Meiring & Myburgh, 2015). Early adopters of AI, such as the technology giants including Amazon, Google, and Baidu were the ones who gained the most competitive advantage from AI. They are investing in AI to improve their business operations, such as optimizing searches and targeted marketing. These early adopters have been using AI technologies such as NLP and machine learning to provide a highly personalized experience for customers.

2018 may be the most popular year for AI. However, AI is far from the answer to every business problem. And its application in actual use cases is still far. According to *the 2018 World Artificial Intelligence Industry Development Blue Book*, AI adoption in industries is still at the infancy stage. Few firms have incorporated Al into their value chain at a large extent. According to CAICT and

Gartner (2018), only 4% of the firms invest on AI and deploy AI technologies. Most firms are still considering AI and making plans for AI.

2.2 Telecom industry and AI

Since the introduction of the telephone in 1876, the telecom industry had gone through a serial of incremental innovation. The earliest AI application in the telecom industry was available in the 1980s and mainly focused on the expert system (Qi et al., 2007). The AI application was applied to improve the operations and maintenance of telecom networks and services. This application triggered the studies on AI applications in the telecom industry. For example, Macleish (1988) demonstrates how the first-generation expert system can help diagnose complex equipment in the telecom industry in an off-line mode. Muller et al. (1993) discuss why AI is an appropriate solution to telecom problems. Seshadri (1996) summarizes the technologies and applications of AI applied by telecom operators and indicates that AI technologies can help solve practical problems in the telecom industry.

After 2000, the focus of the telecom industry switched from basic telephone and Internet services to high-tech and data-centric networks. The change caused the shift of service from voice calls to video and data. With the expansion of the network scale and the development of business types, the telecom industry is constantly facing new challenges and problems. In the digital transformation, the telecom industry encounters huge challenges. On the one hand, the demand for speedier data connectivity, higher resolution, quicker video streaming, and ample multimedia applications keeps growing (Castro, Richart, Baliosian, & Grampín, 2018). On the other hand, threats from fast and highly efficient web-scale companies are getting stronger. The challenges push telecom operators to grow their subscriber bases by offering improved services and new features. The Internet of Things and 5G networks are important roadmaps for the development

of current telecom networks, and the implementation of each technology will bring about major changes to the current network architecture and technology. At the same time, there will be huge challenges in the design, operation, and maintenance of the telecom network. The key issue for telecom operators is how to manage and operate the dizzyingly complex next generation 5G/Internet of Things (IoT) networks. The 5G network is rather complex because it consists of various distributed nodes, dense small cells, millimeter waves, unlicensed spectrum, shared spectrum, and 3G/4G derivative technologies (Xu, 2011; Xu, & Duan, 2018). Only AI can manage and maintain such a complex network. AI with robust data analysis and information extraction capabilities brings new opportunities to telecom networks. As the infrastructure of information communication, telecom networks have enormous space and potential for applying AI technology. How to use the powerful analysis, judgment, prediction and other capabilities provided by AI algorithms to enhance the application of network elements and business systems, and combine AI with the design, construction, maintenance, operation and optimization of telecommunication networks has become an important topic for the telecom industry. Some telecom operators have begun to experiment and deploy AI-driven solutions for customers and their internal operations (Zhang & Lorenz, 2018). Some of them even make AI strategic development plans. For example, AT&T is experimenting with AI as a key enabler for next-generation wireless technology. It expects that 75% of AT&T's network will be virtualized by 2020 (Dano, 2016).

The telecom industry will become an important driving force for the development of AI and a major field for AI applications. Telecom is a capital-intensive industry with high fixed costs (Falch, 1997). Thus, telecom operators must control operating expenses, especially human capital. This article applied special research on sustainable growth, which empirically verified

that operating expenses are strong significantly related to firm sustainable growth. In addition, other than the threat from fast growing Internet giants, telecom operators are facing the challenge of digital transformation as well. Telecom operators must know how to manage and operate the dazzling next generation 5G/IoT network. The market conditions and economic pressures make telecom operators need AI-driven automation solutions urgently in the coming years. On the other hand, 5G can provide a better supporting foundation for AI technology from data and computing power, and greatly promote the application of various terminal usage scenarios of AI. The integration of AI into the telecom network system is a long-term and gradual process. In this process, the degree of intelligence of the network will be from low to high, and the ultimate ideal is to achieve a high degree of autonomy in the network operation process.

At present, academics and industry have successively studied the application of AI in telecom networks to promote the deep integration of AI and telecom network technology. Telecom operators in the world have also begun to explore the application of AI technology, and have achieved good results in some areas. For example, AT&T is investigating how to use AI algorithms to enable drones to check and repair base stations. SK Telecom in South Korea is using machine learning to analyze network traffic to detect anomalies and strengthen network operations. In addition, telecom operators provide many AI services by cooperating with partners. For example, since September 2016, Deutsche Telekom has been working with Amazon to leverage the Amazon AI assistant Alexa, which provides voice capabilities for its smart home platform. In 2016, Chinese Internet giant Baidu inked a strategic partnership with a leading telecom operator, China Unicom, aiming for leveraging their expertise and advantages in online and offline services and improving cooperation on projects in mobile Internet, AI, big data, and telecom services (Xinhua, 2016). So far, China Unicom has 12 joint AI technology laboratories.

Other than Baidu, China Unicom cooperates with JD.com, Iflytek, Alibaba, Tencent, and Xiaomi to develop smart products and services as well as smart applications. In 2018, Nokia and China Mobile established a joint AI/5G lab to research AI applications in 5G networks (Nokia, 2018). Moreover, AT&T teams up with Tech Mahindra to develop Acumos, the industry's first open-source AI platform.

The telecom industry can apply AI technologies in customer experience, network automation, business process automation, new digital services, and infrastructure maintenance. For telecom operators, customer service levels greatly affect customer experience and satisfaction. The customer service system requires much workforce to ensure the timeliness and effectiveness of the customer response. Relying on speech recognition, natural language processing, and face recognition technologies, the emergence of AI provides a new way for telecom operators in the field of intelligent customer service. In specific, AI can help telecom operators improve efficiency in network performance monitoring, predictive performance, and configurations of data routing. The following are the common AI applications in telecom operators.

2.2.1 Customer service chatbots

AI can be applied to customer relationship management systems for automating customer service inquiries, directing customers to the proper agent, and routing prospects with purchase intent directly to the salesperson. For instant messaging, web page interaction and other text customer service channels, using the natural language processing technology of AI, a chatbot can understand the problem semantics, search the relevant knowledge base, and automatically respond. Particularly, AI-driving chatbots can make customer service faster and more scalable. The automatic chatbot can greatly reduce the workload of customer service personnel, divert a large number of common consultations, and improve customer service efficiency. Gartner says 52

percent of telecommunications firms, are already deploying chatbots bolstered by AI to improve customer experiences and services (Osborne, 2019). Vodafone, for example, launched TOBi, the first live AI-based chatbot in the U.K. The chatbot provides faster customer services and handles more than 70% of customer queries (Vodafone, 2017). China Mobile launched its customer service bot Yiwa, which has more than 200 million interactions with customers in one month. Yiwa helps China Mobile save more than 110 million yuan in labor costs (Xinhua net, 2016).

2.2.2 Speech and voice services for customers

AI-based speech and voice services allow customers to explore or purchase media content via spoken words instead of using the remote control (Sehgal, Agarwal, & Rai, 2018). For example, Amazon’s Alexa steppes in as a first mover in intelligent home devices (Chung, Park, & Lee, 2017). Telecom operators plan to have a similarly delightful customer relationship with the help of NLP. In addition, semantic speech analysis can help the quality inspection department timely to detect sensitive complaint keywords and handle customer complaints and dissatisfaction. The customer's consultation and complaint information imply a large amount of feedback on network failure, quality, and service. Through speech recognition technology, a large number of customer service conversations are converted into texts, and the scope and extent of network and service failures in semantics are analyzed through techniques such as NLP to assist the network in processing and repairing. Moreover, NLP can be applied with sentiment analysis technology to predict customer satisfaction, to improve customer service quality, and to optimize customer experience (Kumar, Irsoy, Ondruska, Iyyer, Bradbury, Gulrajani, & Socher, 2016). Some telecom operators promote mobile chatbots by introducing voice assistants. For example, Orange, a French mobile telco, releases an AI-powered virtual assistant called Djingo, which can be controlled by

voice or text. Djingo offers customers an easy and intuitive way to navigate Orange TV, to manage connected home devices, and to make a call or access lots of other services (Orange, 2018).

2.2.3 Network monitoring and management

Because any downtime at anywhere along the telecom line can be extremely costly, telecom operators need to keep watching on their infrastructure and equipment, including cell towers, power lines, and servers. In this way, they can ensure that their networks are reliable and secure. AI can monitor the status of equipment, identify patterns that predict failure, and perform maintenance on a preemptive basis (Xu, Xu, Cai, Jiang, Luo, & Gu, 2017). In self-healing networks, AI can look for patterns, detect, predict, and localize anomalies or other network issues. AI can even take proactive steps to fix the service before customers are impacted (Sennaar, 2018). Because automated networks can predict and route traffic, big events such as the Olympics and Black Friday can be better prepared. For example, Huawei, a telco equipment manufacturer in China, releases SoftCOM AI, which creates self-driving network architecture to help operators create automated networks that never fail and act as a springboard for digital transformation (Zhu, 2018). In addition, with the help of AI, telecom operators can shorten downtime and lower repair costs.

2.2.4 Generic telco AI platforms

Telecom is the infrastructure that is indispensable in modern society. Telecom operators provide not only the large infrastructure for the global world of interconnected things but also AI services. As Anuradha and Sharma (2017) point out, telecom creates ecosystems for the data-driven economy. Open-source AI frameworks and generic platforms may become the norm in telecom (Bay, 2018). Generic telecom AI platforms are going to be used in broader contexts. They support

smarter connections, smart decision-making, and smart services. They also serve the AI industry and the intelligent transformation of industries. The goal of generic telecom AI platforms is to create ecosystems where telecom operators can utilize their workforce and external developers to create AI applications. For example, China Mobile unveiled its first AI-driven platform dubbed Ninth Heaven (in Chinese, Jiutian) in December 2017. This AI platform serves in intelligent customer service, deep learning platform, smart marketing robot, as well as intelligent networking.

At present, leading telecom operators are leveraging AI to process Big Data. Al is a strategic priority for most of the companies because AI has the potential to optimize and automate their network operations, to improve forecasting and optimize sourcing, and to enhance the customer experience. However, telecom operators are still at an early stage of Al adoption in their businesses. Most AI application in telecom networks is still in the stage of academic research and exploration. However, intelligence is one of the ultimate goals of telecom network development. It has great potential in improving network capabilities and has a profound impact on the development of network technology. In the era of AI, the telecom operator is no longer a simple communication carrier and a simple industry derived from it, but a big data platform and carrier that supports the entire intelligent industry. AI adoption is not as simple as plug and play. The AI development strategy, from data collection to organizational architecture design, and how to prioritize AI projects, is as complex as the technology itself. Telecom operators face challenges involving governments, competition, organizational environment, and their expertise to scale AI adoption. Thus, it is still difficult for telecom operators to launch effective AI solutions so far.

2.3 Telcom industry in China

2.3.1 Background

Communication service is a highly regulated infrastructure industry in China. All facilities-based telecom operators in China are state-owned monopolies for years. In 1997, China started to implement reforms and promote competition in the telecom industry. After several rounds of reform and restructuring, the industry now has three dominant national operators: China Mobile, China Unicom, and China Telecom. In 2008, they all became full-service operators, which offer a full range of lined telecom, mobile phones, data connections, and other basic telecom services. These three telecom operators compete for providing telecom services.

Currently, China has one of the largest and most advanced telecom networks in the world, providing strong support for the development of the national economy. The Chinese telecom market has unique characteristics and enormous potential. China is the only country in the world, allowing the coexistence of multiple 3G standards: CDMA2000 for China Telecom, TD-SCDMA for China Mobile, and WCDMA for China Unicom. The three telecom operators were issued 4G license at the end of 2013. They were all set to have the same starting point of offering the service of the 4G mobile network. The purpose is to increase competition among them (Tang & Xia, 2016). As of December 31, 2018, these three operators had 1543 million mobile subscribers and 384 million wireline broadband subscribers(finance.yahoo.com).

China Mobile Limited (CHL) was incorporated in 1997 which provides services including wireline and wireless voice, roaming, broadband Internet service, and value-added services, such as digital applications comprising music, video, and gaming. As the leading mobile services provider in China, China Mobile has the world’s largest mobile network and the world’s largest mobile

customer base (Wojcik & Camilleri, 2015). At the end of 2018, the company serves 925 million mobile subscribers and 157 million fixed broadband subscribers (finance.yahoo.com).

China Telecom Corporation Limited (CHA) offers wireline and mobile telecommunication services, internet access, mobile value-added services, managed data services including the digital data network, frame relay, information consulting services, and other services in China. The company was incorporated in 2002. As of the end of 2018, China Telecom had approximately 303 million mobile customers, and 146 million wireline broadband customers(finance.yahoo.com). China Telecom is actively engaged in 5G technology research and application development and has released 5G technical white papers. The company conducts large-scale network test in multiple cities to adequately prepare for 5G commercial use.

China Unicom (Hong Kong) Limited (CHU) was incorporated in 2000, which is the only telecom operator in China that is listed in Shanghai, New York, and Hong Kong. It offers services includes wireline and mobile phones, Internet-related services, business and data communications services, technical consulting services, lease services for telecommunications networks and other services in China. As of December 31, 2018, it had 315 million mobile subscribers and 81 million wireline broadband subscribers (finance.yahoo.com).

China Tower Corporation Limited (CHWRF), the world's largest telecom operator of mobile phone towers, was founded in 2014 via the merge of the transmission provided by China Mobile, China Unicom, and China Telecom. The company is state-owned as well and mainly engaged in the construction, maintenance and operation of base station supporting facilities, such as communication towers, high-speed rail public network coverage, and large indoor distribution systems. The establishment of China Tower mainly aims to reduce the redundant construction of communication towers and related infrastructure in the telecom industry, further improve the level

of joint construction and sharing of telecom infrastructure, further promote resource conservation and environmental protection, enhance market competitiveness and accelerate transformation and upgrading. On August 8, 2018, China Tower was officially listed on the Hong Kong Stock Exchange, becoming the world's largest IPO in two years (NCBC, 2018). By the end of 2018, the company had a total of 1.948 million sites and an asset size of 315.46 billion yuan (China-tower.com).

With the increasing competition in the telecom industry in China, the three major operators continue to compete fiercely in the 4G mobile subscriber market, and on the other hand, actively expand the wireline broadband market. The profiles of these operators and their market share of main subscribers are shown in Table 1 and Figure 2. The revenue of these operators in 2018 is shown in Figure 3.

Table 1. The Profile of These Four Operators (Data source: Bloomberg and finance.yahoo.com)

Operators	Issue (IPO) Date	Mobile subscribers /the number of sites (million)	Wireline broadband subscribers (million)	Revenue (Billion, CNY)	Full Time Employees
China Mobile	10/23/1997	925	157	736.82	459152
China Telecom	11/15/2002	303	146	377.12	280747
China Unicom	6/22/2000	315	81	290.88	246299
China Tower	8/8/2018	1.948		71.82	18039

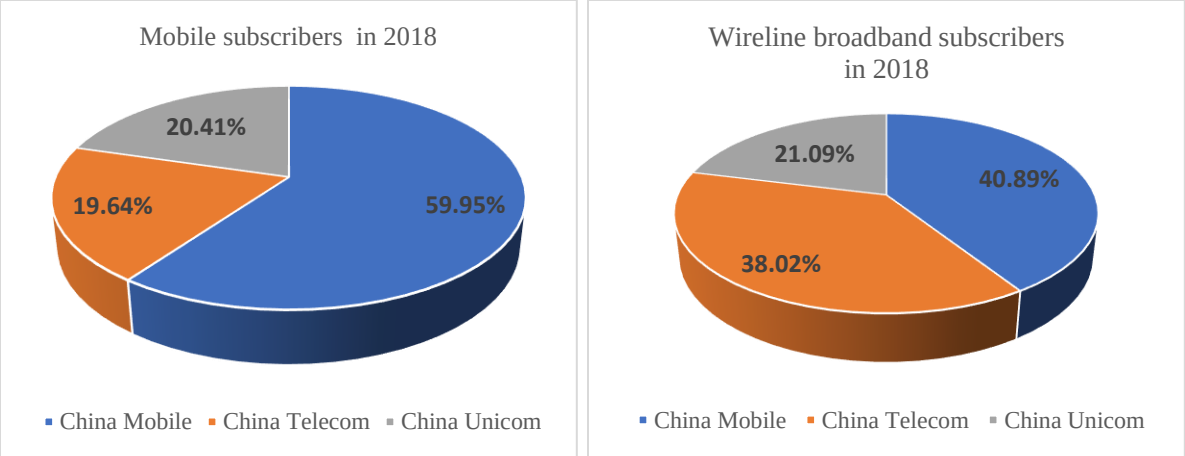

Figure 2. The Market Share of the Main Subscribers of These Three Operators (Data source: finance.yahoo.com)

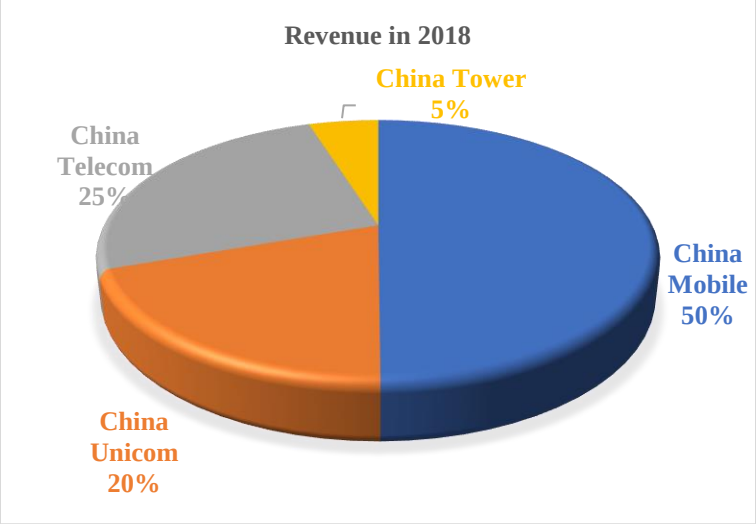

Figure 3. The Revenue of These Four Operators in 2018 (Data source: Bloomberg)

2.3.2 Government policies influence the telecom industry

The Chinese government has majority ownership of these four operators, which are all have established 31 provincial-level branches and municipal-level branches throughout the country. The role of the government focuses on creating boundary conditions, such as setting competition rules,

granting licenses to operators, tariff supervision, inter-network interconnection, and universal service requirements.

In August 2013, the State Council of China issued the “Broadband China” strategy implementation plan, deploying broadband development goals and strategies for the next eight years. The "Broadband China" strategy aims to expand broadband coverage in both rural and urban areas, with urban and rural household broadband speeds reaching 20 megabytes per second (Mbps) and 4 Mbps respectively by 2020, that means to speed up the network and lower the service fees in few years. Since then, the Ministry of Industry and Information Technology has jointly issued relevant special actions for the implementation of Broadband China in conjunction with relevant ministries and commissions every year. Operators have taken action to win national policy and financial support and accelerated the development of 3G communication and fiber broadband networks to expand coverage. As a result, communication capabilities and the number of broadband subscribers continue to increase, which are shown in Figure 4. Under the guidance of the broadband China policy, the length of the optical cable lines of the three operators maintained relatively fast growth. According to the date from the National Bureau of Statistics of China, by the end of 2018, the total length of the optical cable lines has reached 43.85 million kilometers, an increase of 15.3% over 2017. The popularity of fiber optic cable and the rapid growth of fiber access have laid a good foundation for operators to improve service quality and expand service content.

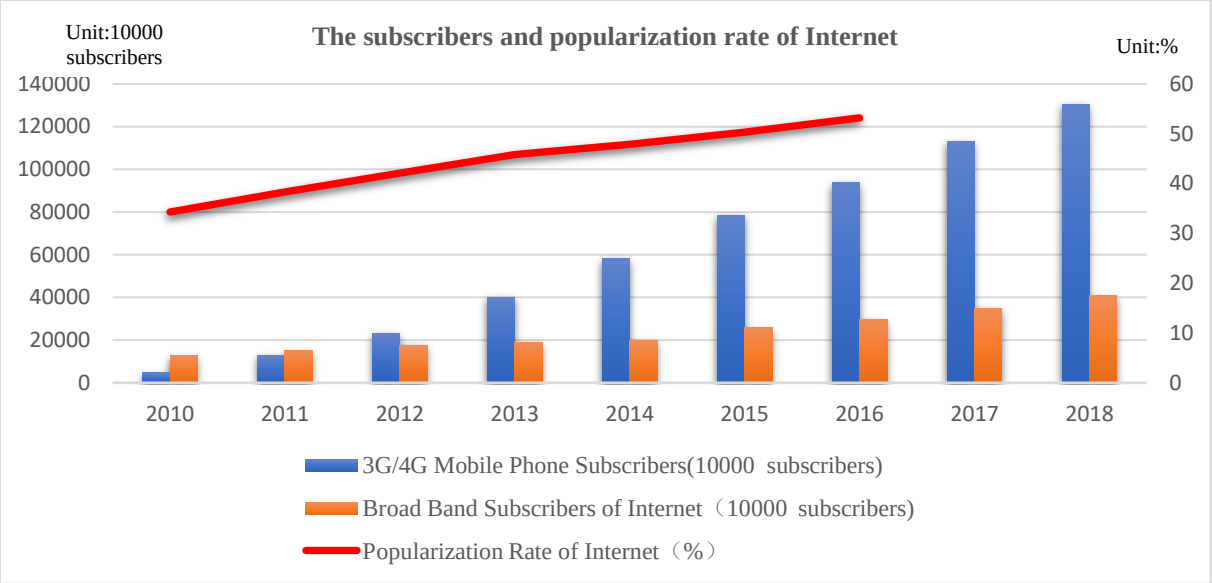

Figure 4. The Subscribers and Popularization Rate of the Internet in China (Data source: National Bureau of Statistics of China and the Ministry of Industry and Information Technology)

From 2016 to 2018, the network speed-up effect is remarkable, and the proportion of high-speed broadband users is greatly increased, which is shown in Figure 5. In 2018, the proportion of users with broadband access rates exceeding 100 Mbps reached 70.3%.

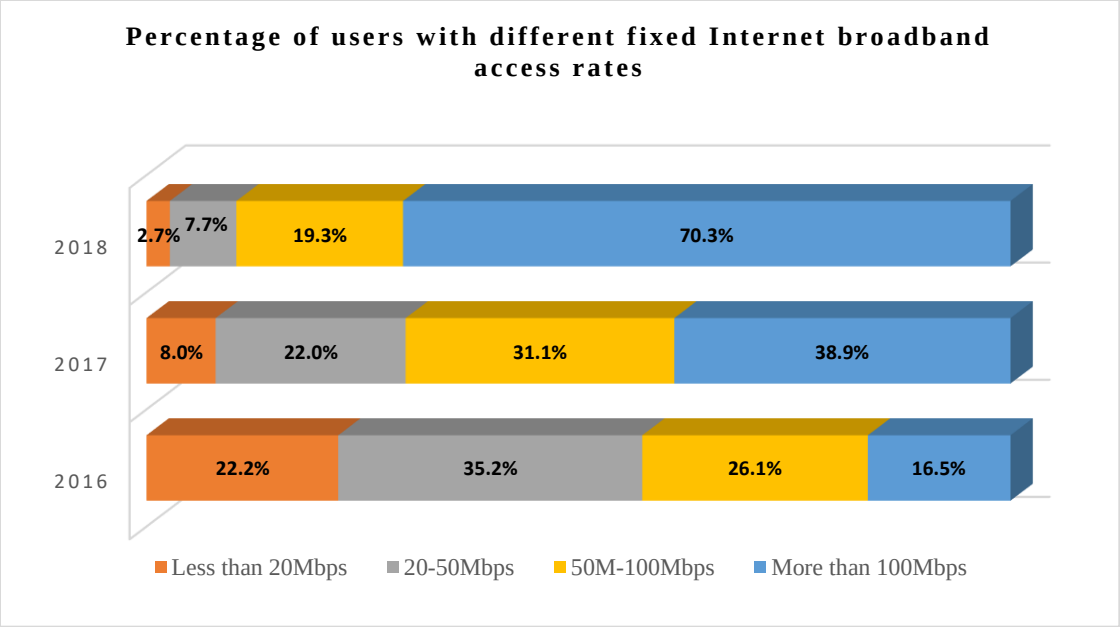

Figure 5. Percentage of Users with Different Fixed Internet Broadband Access Rates (Data source: The Ministry of Industry and Information Technology)

In May 2018, the Ministry of Industry and Information Technology(MIIT) and the State-owned Assets Supervision and Administration Commission jointly issued the "Implementation Opinions on Deepening the 2018 Special Action for Speeding up the Network and Reduce Expenses and Accelerate the New Development of Economic Development", which proposed to cancel the charge of mobile data roaming from July 1 and the average unit price of mobile data should be reduced by more than 30% during the year. Therefore, since July 1, 2018, the three major operators have canceled the domestic mobile phone data roaming charges. This led to an increase in the usage of data plan and a decrease in data charges. In order to avoid revenue reduction, operators integrate national packages, strengthen product and service innovation, promote customer usage, and strive to reduce the impact of policies on business performance. As the unlimited data package is widely promoted by the three major operators, the data consumption of mobile users is exploding. The changes in consumption of the mobile Internet data are shown in Figure 6 and Figure 7. With

the popularity of 4G and the arrival of 5G, the scale of mobile data consumption will continue to grow at a high level in the next few years in China (Deloitte, 2018).

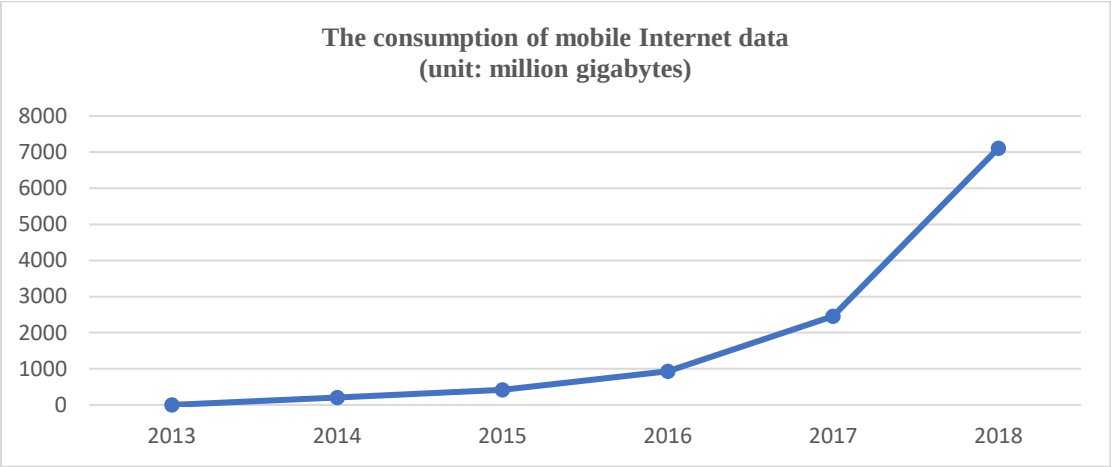

Figure 6. Mobile Internet Data from 2013 to 2018 in China (Data source: The Ministry of Industry and Information Technology)

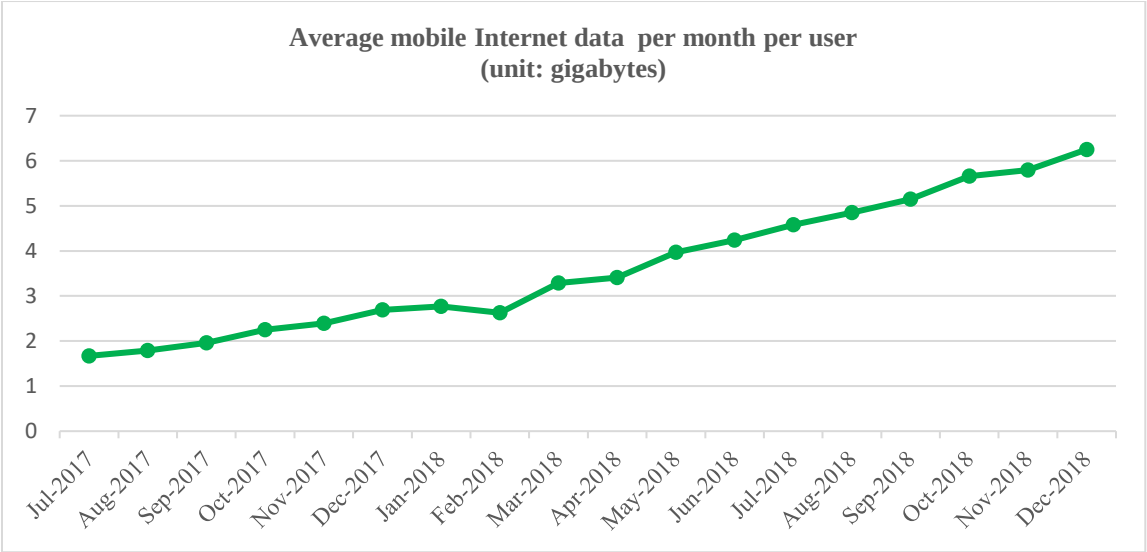

Figure 7. Average Mobile Internet Data Per Month Per User from June 2017 to December 2018 in China (Data source: The Ministry of Industry and Information Technology)

In November 2017, the Ministry of Industry and Information Technology announced the 5G frequency band, marking the gradual entry into the industrialization stage of the development of 5G, and steadily moving towards commercialization. After that, the operators in China began to build the 5G trial network in major cities. In 2018, China Telecom took the lead in conducting 5G field testing in some cities, and it is expected to begin commercial deployment in 2020. In June 2018, China Telecom released *China Telecom 5G Technology White Paper* at Shanghai World Mobile Conference, which comprehensively expounded the 5G technology perspective and overall strategy.

2.3.3 Chinese AI Strategy

In terms of the number of AI companies and talent pools, China is now widely regarded as the second largest AI economy, only behind the United States.

In 2017, the Chinese State Council issued A Next Generation Artificial Intelligence Development Plan, focusing on the financing and development of AI to improve the economy and marking the development of AI has become a national strategy, on its way to becoming the leading AI superpower by 2030. The government prepares a multi-billion-dollar national investment plan to support the "moonshot" project, start-ups and academic research in the AI field which is a continuation of the “13th Five-Year Plan” and the “Made in China 2025” industrial plan.

In the same year, the Ministry of Industry and Information Technology in China released the Three-Year Action Plan for Promoting Development of a New Generation Artificial Intelligence Industry (2018-2020), which outlines major areas and specific industries to focus on AI development and plans to implement a conducive infrastructure.

The government has invested more than $1 billion in domestic startups through the “Government Guidance Fund” (GGF) established by local governments and state-owned enterprises (Ding, 2018; Faggella, 2019), which indicates that the government has already played a significant role in funding AI ventures. By 2025, China plans to achieve core AI industry and AI-related industry gross outputs more than $60.3 billion and $754 billion, making China a global leader in many AI fields (Ding, 2018; Faggella, 2019). By 2030, China seeks to become "the world's leading AI innovation center" with the gross outputs of the core AI industry in China exceeding $150 billion.

The telecom industry is one of the fastest growing industries in the world. Telecom operators will play an important role in the commercial chain of AI commercialization. They are users of AI technology, the core drivers of the AI industry, and the providers of AI services. AI is the key to future service, whether it is 5G or IoT. The strong support from the government for the development of AI will inevitably bring huge opportunities and development prospects to the telecom operators in China.

2.3.4 Challenges and opportunities for operators

In China, the three state-owned telecom operators are the backbone of the broadband Internet and provide connectivity, whereas non-state-owned firms provide Internet-based applications and services (Wu, 2015). Non-state-owned firms rely on the Internet connectivity provided by the three state-owned operators to offer consumers their services, including search engines, social networks, video, and messaging. This means that the state-owned telecom operators provide non-state-owned firms a platform, the Internet, on which non-state-owned firms develop services for consumers. Sate-owned firms and non-state-owned firms play different roles in serving consumers. However, some services provided by non-state-owned firms challenge the role of the three state-owned operators. For example, WeChat is a multi-purpose messaging, social media, and mobile payment

application developed by Tencent shrinks the three state-owned operators' revenue generated by short text messages and voice calls. Although the three state-owned operators propose to collect charges on WeChat, the Chinese government does not approve (Wu, 2015).

Because the content and the connection of the Internet are operated separately, the state-owned operators do not have any control over the applications and services on the Internet in China. Thus, they seek disruptive technologies that can bring them business opportunities. According to Tang and Xia (2016), commercialized 5G networks will be available in China by 2020. The 5G networks will help the state-owned operators move beyond connectivity and further collaborate with various sectors, such as finance, transport, retail, and healthcare, to deliver new services. For the 5G networks, the key performance indicators such as the transmission rate, transmission delay, and connection scale of the network are constantly improving. The application scenarios are becoming more and more abundant. At the same time, the network is more and more complex, and the flexibility requirements are getting higher and higher, which brings unprecedented challenges to the operation and maintenance of the 5G network. There is no doubt that AI will help accelerate the construction of 5G networks. As one of the most advanced technologies, AI needs support from communication networks, especially high-speed wireless networks such as 4G and 5G, which are related to application systems and infrastructure. AI and the communication network are interconnected and become a sufficiently intelligent society. Accordingly, AI will be boosted by the 5G network. 5G will provide high-quality channels for typical applications of AI, provide more massive data for AI, and provide targeted customization capabilities for AI. The state-owned operators need to explore new business models by deploying effective AI solutions based on 5G networks. In other words, the 5G networks expand the state-owned operators' role from the

providers of network infrastructure and data pipelines to the providers of massive data and AI computing capabilities (Wu, 2015).

2.3.5 Applications and trends of AI in telecom operators

Other than the impressive economic growth in the last four decades, China has made tremendous strides in many fields including AI. At present, the IoT, software definition/virtualization, and 5G have become important directions for the development of communication networks. The realization of each technology poses greater challenges for the construction and operation of the network. Applying AI technology to the network, using the capabilities of analysis, judgment, and prediction of AI algorithms, empowering network elements and business systems, and combining them with the work content of communication networks have become the only way for the development of the communication industry. "AI+ communication" is the inevitable direction for the future communication network upgrade and the digital transformation of operators. Currently, the major telecom operators in China have already deployed AI applications.

2.3.5.1 China Mobile

China Mobile has also made a large number of technical reserves and applications in intelligent services, intelligent markets, intelligent security, and intelligent entertainment. In recent years, China Mobile has increased its investment in AI technology research and development.

In 2016, China Mobile launched its self-developed intelligent robot customer service "Yiwa". It has the ability to communicate and service based on natural language, which can be applied to traditional channels such as WeChat, website and other Internet channels, such as SMS and hotline, to meet complaints, information inquiry, greetings and other needs of customers, achieving "24 hours" online and "all-weather" service and further enhancing the customer service experience

(GG-robot, 2016). Based on machine learning, Yiwa can be applied to multiple scenes. For example, it can accurately understand customer intentions through cross-examination, verification, and analyze customer sentiment fluctuations based on multiple dimensions such as language and speed of speech. At the same time, it can also provide payment services, give weather, geography, humanities and other information, and support Chinese, English, and other multilingual translation. At present, the monthly interaction of Yiwa exceeds 200 million times, which is equivalent to the workload of 1000 customer service personnel, the accuracy rate is 93%, and the access customer channel is over 170, which indicates that Yiwa has become the largest intelligent interactive robots for customers in the world (CCTIME, 2018).

China Mobile released its first AI-driven platform called Jiutian at the China Mobile Global Partner Conference in 2017. This AI platform is adopted not only by the telecom industry for improving operators' operations, networks, and services, but also by other industries in end-to-end AI application solutions, intelligent customer service, deep learning platform, intelligent marketing robot, and network intelligence. The platform provides algorithms, computing power, and data at the infrastructure layer, offers basic capabilities such as voice, language, image and video, data analysis, and data management at the core capability level, and focuses on intelligent services, smart markets, intelligence network, intelligent management of the four business areas at the application layer. So far, in Shanghai, Jiangsu, Zhejiang and other provinces, through the use of the basic capabilities of the nine-day platform, combined with local specific business needs, China mobile has developed a variety of AI applications such as intelligent marketing robots, network intelligence, automatic source tracking of fault sources, and automatic quality inspection.

At the beginning of 2018, China Mobile and four other global operators, including AT&T, Deutsche Telekom, NTT DoCoMo, and Orange, jointly announced the establishment of "O-RAN

Alliance," which is the open unlimited access network alliance to help shape the next generation of radio access networks(RAN). The alliance aims to lead the industry towards open, interoperable interfaces, RAN virtualization, and big data-enabled RAN intelligence. In addition, China Mobile and Nokia signed a memorandum of understanding to jointly establish an AI and ML laboratory in Hangzhou for delivery of new Edge Cloud and 5G services at the recent Sino-German Economic Forum. They will work together to foster an open RAN and 5G ecosystem with third parties to conduct technology field trials and demonstrations and to optimize networks for the delivery of services.

China Mobile announced that it has built the first 5G smart highway for autonomous cars and AI traffic monitoring. The infrastructure is currently under construction in Wuhan. China Mobile has installed 31 5G base stations in Wuhan to support the program, and it expects to add 2,000 sites in 2019.

2.3.5.2 China Telecom

In recent years, China Telecom has been committed to become a leading integrated intelligent information service operator. The company actively develops and promotes technical standards and industrial development in the field of network AI at home and abroad and achieves remarkable results. In 2017, China Telecom jointed industry partners and established the world's first network AI standard working group called Experiential Networked Intelligence (ENI) at the European Telecommunications Standards Institute (ETSI), and externally released the world's first international technical standard for AI. The standard defines three categories and 14 subcategories of network AI applications, covering business, network, function, operation and maintenance, and legal fields. It is the first standard officially released by ETSI ENI and the first standard in the world for the demand of network AI.

In April 2018, the China Artificial Intelligence Industry Development Alliance (AIIA) officially released the White Paper on Artificial Intelligence Application in Telecom Networks. The white paper is led by China Telecom and co-produced by several domestic industry partners. The white paper studies and thinks about network AI from the perspective of technology application. The definition and connotation of network AI are given for the first time. It summarizes 11 typical application scenarios of network AI, which involves fault alarms, performance optimization, pattern analysis, orchestration management of multiple professional networks. The white paper proposes a future network AI application framework, which indicates the driving force, demand, vision, and direction of AI technology application in the operator's network and lays a foundation for the subsequent development of the solution for application scenarios.

China Telecom is actively deploying all kinds of emerging technologies such as AI and 5G. It has developed an open AI platform Dengta with its partners. In January 2018, this platform was officially released which can provide DTaas deep learning training service. DTaaS is a one-stop deep learning platform based on AI model algorithm set and computational cluster formation. It uses a simple AI algorithm to carry out model training, evaluation, and prediction. DTaaS can significantly reduce the threshold of AI research and development, bringing unlimited possibilities to the AI industry, including security, smart home, finance, autonomous driving, medical imaging diagnosis, AI speakers, intelligent animal husbandry. Moreover, the intelligent customer service robot Xiaozhi is integrated with deep learning of neural network, speech recognition, natural language processing, and contextual scene interaction. It can provide 24/7 intelligent response service to customers in human-computer interaction mode. On average, it serves more than 40 million customers a month.

China Telecom and Nokia Bell jointly signed a strategic cooperation agreement on AI at the China International Information and Communication Exhibition in 2018. The two companies will integrate Nokia's leading AI/ML technologies, as well as 5G cloud and edge cloud network products and solutions, to "power" China Telecom's end-to-end intelligent network and optimize 5G network deployment, management and application efficiency. The two parties will also jointly promote the application of AI in mobile communication networks, and further promote the research, verification, display, and promotion of key technologies of AI.

2.3.5.3 China Unicom

China Unicom has accelerated the transformation of Internet operations and built an intelligent core business support platform, which can achieve nationwide landing and rapid iteration. China Unicom also works with Baidu, Iflytek, and Bonfire to develop AI applications.

In November 2016, Chinese Internet giant Baidu signed a strategic partnership with China Unicom to apply AI and other leading technologies to future products and services. The two companies leverage their expertise and strengths to collaborate with projects on mobile Internet, artificial intelligence, big data, and telecommunications services. The initiative is an important step in cross-industry cooperation between Internet companies and telecom operators, in line with the government's "Internet +" proposal to upgrade traditional industries with IT technology. In April 2019, the two companies released an AI assistant called Xiaodu1C China Unicom customized version which focuses on family scene applications, with excellent remote video calling, voice calling, and camera capabilities, allowing users to connect to distant families at any time. Particularly, it has child mode, which includes massive and quality audio education resources for children. This smart product has become the control center for a new generation of smart families.

The cooperation between China Unicom and Iflytek aims to develop AI applications for the intelligent terminal industry chain. China Unicom also works with Bonfire developing AI applications for smart cities as well as promoting standards. In the medical field, China Unicom and Tencent and other partners have launched a medical image cloud solution for medical imaging applications, using image recognition and deep learning technology to automatically identify the lesions of patients with CT, MRI, and other medical images in order to help doctors to improve the efficiency of diagnosis. In order to deploy AI-based managed services solutions to improve network quality and consumer experiences, China Unicom and Ericsson signed an agreement to jointly establish a mobile network AI lab to conduct comprehensive research on AI applications for network design and optimization services in April 2019. The AI laboratory is in line with China Unicom's intelligent transformation of network operation and maintenance strategies and supports operators' efforts to promote research algorithms and innovation.

As a pioneer of 5G innovative applications, China Unicom has actively deployed in vertical industries such as medical health, industrial manufacturing, transportation, security, education, and energy. In 2019, China Unicom released " the Integrated Water and Sky 5G UAV Intelligent Inspection" product. Based on 5G network's large bandwidth data transmission, massive connection and ultra-low latency remote control capability, this product combines the advantages of underwater drones and aerial drones, and uses cloud computing, AI and other technologies to achieve fully automatic water conservancy inspection, which comprehensively improves the level of water management intelligence in the fields of water resources management, water ecological restoration, water environmental protection and water disaster prevention.

China Unicom has previously conducted a series of explorations on the intelligence of various stages of network construction and operation. At the MWC Shanghai Exhibition of the World

Mobile Communications Conference in June 2018, China Unicom released the CUBE-NET 2.0+AI application framework, which is designed to be characterized by ultra-wide flexible pipelines, ubiquitous broadband access, cloud access and interconnection, and cloud-based network services, and further introduces AI technology to create a new network that is intelligent, agile, intensive, and open. In addition, China Unicom officially established the Intelligent Network Center in 2018 to promote the intelligent and software transformation of the network. In March 2019, the Intelligent Network Center of China Unicom initiated the establishment of the Network AI Forum, which will provide a platform for exchanges and cooperation between industry, academia and research institutes, promote the application of enterprise AI products in the operator network, and promote the efficiency of operators' networks, the virtualization of network elements, and operational intelligence. The forum will hold three seminars in June, September and December 2019 respectively, and jointly explore experts in various fields to discuss how to apply AI technology to communication networks to improve the intelligence level of communication networks.

2.3.5.4 China Tower

China Tower actively opens up resources to help railway intelligent construction. In November 2018, China Railway Corporation and China Tower signed a strategic cooperation agreement. In order to deepen resource sharing and strengthen strategic coordination, the two sides jointly create a "high-speed railway + mobile broadband" quality project to ensure that the "high-speed rail opening with the smooth communication," to provide better travel experience and network experience for the passengers.

China Tower chose Alibaba as its strategic ally in 2018. They implement in-depth cooperation in cloud computing and big data. In specific, China Tower provides Alibaba support for their IoT

construction. Alibaba relies on the resource from China Tower to explore 5G, autonomous driving, car networking, new energy, and smart devices. The two parties will also strengthen cooperation in corporate procurement, asset management and disposal, smart office, advertising marketing, cultural entertainment and map services, and big data analysis based on their resources and needs.

In January 2019, China Tower and Zhejiang Daoji Agricultural Technology Development Co., Ltd. signed a strategic contract on smart agriculture construction, 5G network coverage, smart streetlights, and intelligent control. China Tower will provide network technology support for their project, of which 5G networks will be applied to agriculture for the first time. The cooperation will establish an online laboratory to store and test the whole process of agricultural experiment and planting in the form of data, combine the new technologies such as model construction and big data processing to formulate the growth model and dynamic prediction of a certain characteristic agricultural product, provide online teaching experiment platform, and contribute to the development of modern agriculture.

In August 2018, China Post and China Tower signed a strategic cooperation agreement. China Tower will give full play to the advantages of site, power, maintenance monitoring platform and business cooperation ecological resources, and provide China Post with comprehensive solutions such as video surveillance and smart materials, multi-domain data information, advertising and other services; China Post will open its office and business premises as a public service facility to China Tower as a communication facility site resource, and rely on its strong delivery network resources, as well as comprehensive service capabilities such as warehousing, transportation and distribution to fully utilize rich supply chain logistics industry experience, providing logistics services of warehousing and transportation for China Tower.

China Tower also launched a "one tower multi-use" solution that integrates video surveillance, meteorological monitoring, atmospheric monitoring, land environmental monitoring, ocean monitoring, earthquake emergency rescue, smart WiFi, streetlights lighting, earthquake emergency rescue, promoting the transformation of "communication tower" and "social tower" and deepening sharing across industries. China Tower helps to complete the 4G+5G mobile communication infrastructure construction of Beijing World Expo 2019. It includes 12 large base stations inside and outside the park, 74 small base stations, and 114 smart light poles. It fully covers 5G signals for 11 pavilions with an area of more than 200,000 square meters. The 12 outdoor macro base stations in the park not only carry the signal coverage of 9 sets of 3G/4G/5G of the three operators but also carry the 800M private network, the 1.4G private network, and the park high point security monitoring and control of landscape lighting wireless bridge equipment services. The communication tower becomes a social tower, achieving a multi-purpose tower.

In short, for AI, operators have landed in technology, platform, and application, and most of the initiatives are developed together with partners. Although the major telecom companies in China have stepped into the field of AI, the adoption of AI is still in the early stage. It takes time before AI is strategically deployed and sophisticated commercial applications of AI are available.

2.4 The theoretical framework for AI adoption

2.4.1 Literature of IT adoption

Adopting new technologies is one effective approach to achieving business success (Gefen & Straub, 2000; Syeda, 2018). Innovative IT or new system adoption has largely been studied in previous studies at the individual level and the organizational level (Oliveira & Martins, 2011). For individuals' practices in technology acceptance, the theory of reasoned action (TRA) (Fishbein

& Ajzen, 1975) provides profound insight into how a person's behavior is influenced and steered by their attitudes and norms. Ajzen improves TRA and proposes the theory of planned behavior (TPB) (Ajzen, 1991), which states that attitude toward behavior, subjective norms, and perceived behavioral control, together shape an individual's behavioral intentions and behaviors. Based on TRA, Davis (1985) proposes the technology acceptance model (TAM) to ascertain what factors cause people to accept or reject information technology. It suggests that when users are presented with new technology, several factors influence their decision about how and when they will use it (Davis, 1989). Numerous studies have validated TAM and confirmed the relationship between behavioral intentions and actual system use (King & He, 2006; Mohammadi, 2015; Venkatesh, Morris, Davis, & Davis, 2003; Wallace, & Sheetz, 2014). However, TAM does not include some quality factors of an IS or some social influences. Thus, the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) is presented to explain users' intentions to use an information system and subsequent usage behavior. Many of the individual level IT adoption studies explore what factors affect individuals' decision regarding the usage of a particular technology or system, such as Web 2.0 technologies (Ajjan & Hartshorne, 2008), mobile healthcare systems (Wu, Wang & Lin, 2007), and online banking (Lee, 2009; Yiu, Grant & Edgar, 2007).

At the organizational level, Tornatzky and Fleischer (1990) propose the technology-organization-environment framework (TOE) to explain how technological and environmental factors affect organizations' decisions regarding technological innovation adoption. Enlightened by the TOE, some scholars explore what factors affect organizations' IT adoption. For example, Cristiano, Liker, and White (2001) survey to investigate the application of quality function deployment (QFD) in more than 400 companies in the U.S. and Japan. They find that organizational characteristics, such

as motivation, management support, and data sources, positively affect the successful application of QFD. Quaddus and Xu (2005) conduct a qualitative field study and identify four factors affecting the adoption and diffusion of knowledge management systems (KMS) in organizations, namely organizational culture, managerial support, benefits to individuals, and dream of KMS. Co, Patuwo, and Hu (1998) analyze 27 management variables associated with the human factors that affect firms' adoption of advanced manufacturing technology (AMT). Kosaroglu and Hunt (2009) find that technical, leadership, managerial, and administrative skills contribute to the success of new product development (NPD) projects in the telecom industry. Oliveira and Martins (2011) review the research models regarding IT adoption at the organizational level, including TOE framework (Tornatzky & Fleischer, 1990), diffusion on innovation (DOI) theory (Rogers,1995), institutional theory (Scott & Christensen, 1995), and electronic data interchange (EDI) framework (Iacovou, Benbasat, & Dexter, 1995).

2.4.2 Models and theories of IT adoption

TAM, TPB, and UTAUT have been widely applied in IT adoption research. However, they are applicable for studies at the individual level. In contrast, DOI and the TOE framework are the two theories applied widely in IT adoption research at the organizational level (Chong, Ooi, Lin, & Raman, 2009; Oliveira & Martins, 2011).

DOI Theory (Rogers,1995) is one of the oldest social science theories. It originates from communication to explain how an idea or product gains momentum and spreads through a particular population or social system over time. Rogers defines that diffusion is the process of spreading innovation between social system participants over time (Rogers, 1995). According to the theory, innovation should be widely adopted to achieve development and sustainability. Rogers points out that people who adopt an innovation early have different characteristics than people

who adopt an innovation later. He categories adopters into five categories, namely innovators, early adopters, early majority, later majority, and laggards. Moreover, strategies for different categories of adopters should be different when promoting innovation. Rogers (2003) notes that innovation is the process of communication using various channels within the social system. Three factors affect the adoption of innovation in organizations, namely individual (leadership attitude toward change), internal organizational structure (centralization, complexity, interconnectedness, the number of employees, and organizational slack), and external characteristics (system openness) of the organization (Oliveira, Thomas, & Espadanal, 2014; Rogers, 2003). The process of diffusion of innovations is influenced by four elements: innovation characteristics, communication channels, social system, and time. DOI posits that diffusion of a technology innovation depends on innovation characteristics, such as relative advantage, complexity, compatibility, observability, and trialability (Rogers, 1995; Oliveira & Martins, 2011), and these five factors have varying degrees of effect in the five adopter categories. It emphasizes that individual and organizational characteristics are the predictors of organizational innovation. Butler and Sellbom (2002) verify Rogers' points and find that factors, such as the characteristics of the innovation itself, and numerous sociological, organizational, psychological, and economic variables, impact the adoption and diffusion of innovation in organizations.

The TOE framework was created by Tornatzky and Fleisher (1990), which describes the factors that influence technology adoption. The TOE framework identifies three aspects of the firm's context that influence the process of technological innovation: technological context, organizational context, and environmental context (Tornatzky & Fleischer, 1990). The technological context includes the internal and external technologies that are relevant to the firm. The organizational context refers to the characteristics and resources of the firm. The

environmental context comprises market elements, competitors, and the regulatory environment. Therefore, TOE is viewed as a more comprehensive lens for the study of the adoption of IT innovations at the organization level (Yang, Kankanhalli, Ng, & Lim, 2013). It makes the DOI theory be able to explain intra-firm innovation diffusion (Hsu, Kraemer, & Dunkle, 2006). It is also not limited by industry and company size (Wen & Chen, 2010). Although specific factors identified within the three contexts may vary across studies, TOE has been applied successfully as key contextual elements that determine new IT adoption at the organization level (Baker, 2012; Oliveira & Martins, 2011). A significant number of studies based on the TOE framework examine the success factors affecting IT adoption (e.g., Chang, Hwang, Hung, Lin, & Yen, 2007; Chau & Tam, 1997; Kuan & Chau, 2001; Zhu, Kraemer, & Xu, 2003).

2.4.3 The theoretical framework for AI adoption

Currently, some studies examine AI technologies applied in certain areas (e.g., Li, Zhao, Zhou, Ding, Chen, Wang & Zhang, 2017; Oyelude, 2017; Simou, Tiligadis, & Alexiou, 2013). Other studies explore the theoretical foundation for AI (Murphy, 2018; Zou, 2015) and applications of AI (Kouziokas, 2017; Qiu, 2018). However, few studies investigate AI adoption, particularly at the organizational level. For example, Alsheibani et al. (2018) propose a research framework for AI adoption, but this framework lacks validation over a set of organizations to identify factors that impact AI adoption. Moreover, hypothesis tests and empirical validation are missing in their study.

In the IS field, publications with the topic of AI are also very seldom. The association for information systems (AIS) provides the list of senior scholars' basket of journals which includes top eight journals in IS field: European Journal of Information Systems, Information Systems Journal, Information Systems Research Journal of AIS, Journal of Information Technology, Journal of MIS, Journal of Strategic Information Systems, and MIS Quarterly. Papers published

from this list journals were also reviewed, few of them are related to AI research. Several papers study early AI applications such as decision support systems (Lee,1988; Steiger,1998) and expert systems (Coats, 1991). Only four papers talk about AI technologies or applications which are shown in table 2.

Table 2. Publications Related to AI from Top Eight Journals in IS Field (from 2000 to 2019)

Journal name	Topic	Authors and year
Journal of Information Technology	The development of AI	(Aleksander, 2004)
Journal of Information Technology	Robots	(Aleksander, 2017)
The Journal of Strategic Information Systems	knowledge management and AI technologies	(Fowler, 2000)
Journal of Management Information Systems	Machine Learning	(Sun Yin, Langenheldt, Harlev, Mukkamala, & Vatrapu, 2019)

The ubiquitous nature of AI and the lack of research on AI adoption at the organization level preclude building on existing theories directly. AI adoption is a complex undertaking that requires not only the purchase of software and hardware but also appropriate infrastructure and resources over a long time. However, no empirical assessment of AI adoption is available so far. Therefore, research is required to consider the factors that affect the propensity of AI adopt and the specific organizational capability and environmental circumstances of an organization. The review of studies on AI adoption suggests that the TOE framework provides a good starting point to investigate AI adoption not only because it highlights the specific context where the adoption process takes place, but also because it can be applied to evaluate the factors that affect AI adoption. Accordingly, this study chooses the TOE framework as the theoretical foundation. In addition, because scholars integrated the TOE framework with the DOI theory to investigate IT adoption (Oliveira & Martins, 2011), this study follows this approach to examine AI adoption. As

introduced earlier, the TOE framework consists of technological context, organizational context, and environmental context.

The technological context refers to the attributes of technological innovation, technical expertise, and technology portfolio (Rogers, 2003; Yang et al., 2013). The attributes of IT are important factors that influence the IT adoption process (Chang, Hwang, Yen, & Lian, 2006; Raymond,1990). They include perceived benefits and perceived barriers (Chau & Tam, 1997; Kuan & Chau, 2001), technology integration (Li & Zhou, 2013; Oliveira & Martins, 2008), technology readiness (Pan & Jang, 2008), and IT infrastructure (Pan & Jang, 2008; Teo, Ranganathan, & Dhaliwal, 2006; Zhu et al., 2003). Rogers (1995) argues that the diffusion of a new technology depends on some innovation characteristics of this technology, such as relative advantage, compatibility, complexity, trialability, and observability. When relative advantage, compatibility, trialability, and observability of a new technology increase, the rate of its adoption rises (Rogers, 1995). Among these innovation characteristics, trialability and observability are not widely applied in studies on IT adoption (Chong et al., 2009; Oliveira, Thomas & Espadanal, 2014; Zhu, Dong, Xu, & Kraemer, 2006). Other than innovation characteristics, three technological factors, including relative advantage, compatibility, and complexity, are found to affect IT adoption (Chong et al., 2009; Li, 2008; Lim, 2009; Thong, 1999; Wang, Wang, & Yang, 2010; Zhu, Dong, Xu, & Kraemer, 2006). Based on these kinds of literature, innovation characteristics and technological factors play a role in IT adoption.

The organizational context refers to an organization's characteristics that enable it to combine resources for improving its performance. The characteristics include culture, strategies, managerial skills, technical skills, and personnel factors (Teece, Pisano & Shuen, 1997; Yang et al., 2013). Organizational factors include the structure and processes of the organization, limiting or

promoting the adoption and implementation of innovations (Chau & Tam, 1997). Based on resource-based theory which views how firms' available resources are combined in effective growth strategies and their diversification (Wernerfelt, 1984), Garrison, Wakefield, and Kim (2015) point out that leveraging organizational capabilities sufficiently can help firms to establish and sustain competitive advantages, and further positively affect their implementation of cloud computing. Raymond (1990) notes that organizational size, maturity, resources, time frame, and IS sophistication are related to information system success. Nikolaeva (2006) identifies organizational readiness and external influences as the main drivers of e-commerce adoption in the retail sector. Other organizational factors are founded to play a role in IT adoption, including formalization of system development and management (Chau & Tam,1997), IT training program (Oliveira & Martins, 2008), management level for information (Liu, 2008), firm size (Liu, 2008; Pan & Jang, 2008; Zhu et al., 2003), managerial support (Teo et al., 2006), and organizational compatibility (Lin & Lin, 2008).

The environmental context refers to the external arena where firms conduct business, their ability to access resources provided by others, and their interaction with the government and other companies. In specific, the environmental context includes the competitive, legal, and regulatory environment as well as the market where firms operate (Yang et al., 2013). These external factors not only provide opportunities for IT innovations but also have constraints on IT innovations. Ettlie (1983) points out that the greater the competition between companies, the more likely the adoption of innovation. Intense competition can stimulate the rapid spread of innovations and companies are more likely to take aggressive technology policies when they confront with a high degree of market uncertainties (Chau & Tam, 1997; Mansfield, Rapoport, Romeo, Wagner & Beardsley, 1977). Chang et al. (2006) find that government involvement through policies and support can

influence firms' decision of new systems adoption to a large extent. Other environmental drivers are identified by previous studies as well, including government involvement (Chang et al., 2006), regulatory policy (Pan & Jang, 2008), industry pressure (Kuan & Chau, 2001), market uncertainly (Chau & Tam, 1997; Teo et al., 2006), and competitive pressure (Oliveira & Martins, 2008; Pan & Jang, 2008; Zhu & Kraemer, 2005).

3. RESEARCH MODEL AND HYPOTHESES

The literature review indicates that there is limited knowledge about the enabling factors leading to organizations' adoption of AI, and how these factors inter-relating and influencing the decision of deploying AI. As such, this study proposes a research model by integrating the TOE framework and DOI theory to explore further the success factors that affect AI adoption at the organizational level. Particularly, this study categorizes the success factors into innovation attributes of AI, organization capability, and external environment. As shown in Figure 8, factors in the category of innovation attributes of AI are compatibility, relative advantage, and complexity. Factors in the category of organization capability are managerial support and technical capability. Factors in the category of the external environment are government involvement, market uncertainty, competitive pressure, and vendor partnership.

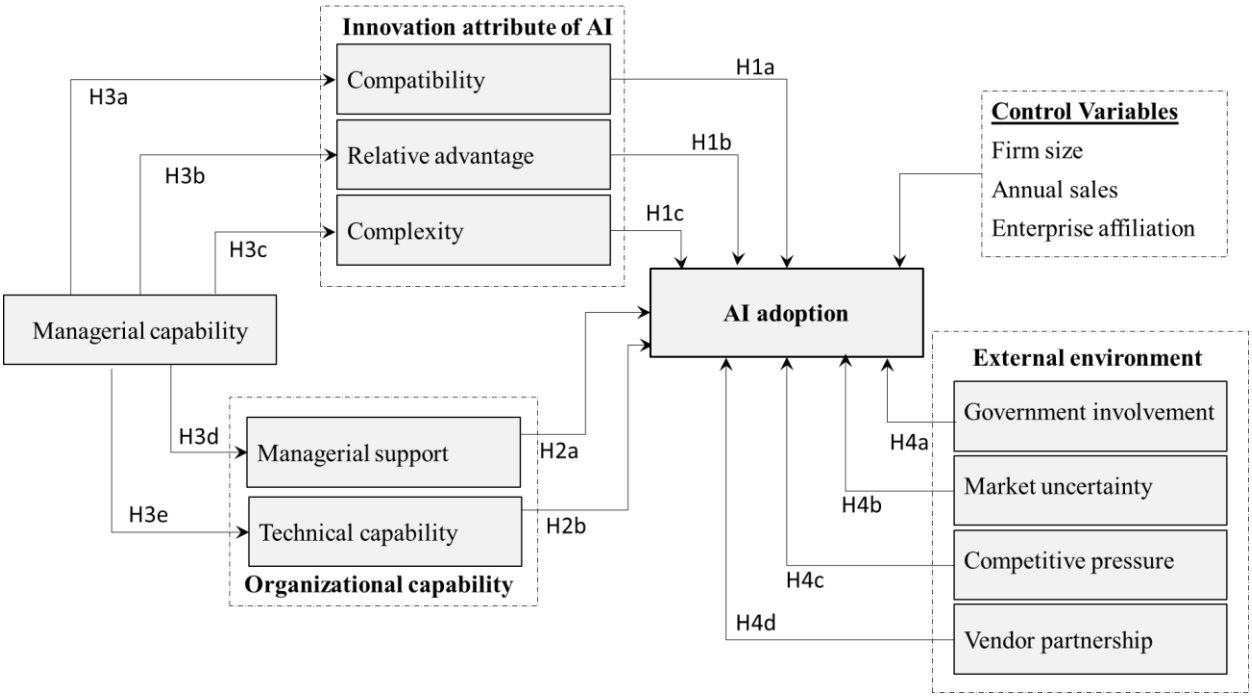

Figure 8. Research Model for AI Adoption

3.1 Innovation attributes of AI

Innovation attributes of AI illustrate the critical factors of AI adoption from the technological context aspect. The impact of innovation characteristics on the innovation process has been studied extensively in existing literature (Chau & Tam,1997; Kwon & Zmud 1987). Although Rogers (1995) identifies five innovation characteristics in DOI theory, namely compatibility, relative advantage, complexity, trialability, and observability, only the first three are found consistently related to innovation adoption at the organization level (Tornatzky & Fleischer, 1990; Wu et al., 2007).

Compatibility

Compatibility is an important determinant of innovation adoption (Azadegan & Teich, 2010; Chong & Bauer, 2000; Dedrick, & West, 2004; Oliveira et al., 2014). It refers to the extent to which the innovation and its ability to provide value and experience while consistent with the needs of the potential adopters (Rogers, 1995). DOI theory points out that the compatibility of innovation with experiences and requirements is positively related to the innovation adoption. A high level of compatibility can result in preferable adoption. In other words, the greater the compatibility, the faster the adoption (Wu et al., 2007). If AI technology is considered to be compatible with current work practices, the organization needs to make a few adjustments and changes, and employees are likely to use it because incompatibilities usually require significant adjustments to the process, which often needs a lot of learning and imply more resistance to adoption. AI technologies, especially machine learning, require massive data (Huang, Zhu, & Siew, 2006). Because AI enables firms to analyze the data they collect and store, AI technologies can be

combined with firms' data resources. When firms transform their network architectures into software-defined networking with virtualization technologies that enable automation, AI can leverage these capabilities to the networks and make them self-diagnose, self-heal, and self-orchestrate. Moreover, the combination of 5G and AI will facilitate firms to achieve digital transform successfully (Li, Hou, Yu, Lu, & Yang, 2017). Comparing with existing technologies, AI technologies have better compatibility with firms' network software and hardware. If AI technology is compatible with existing IT environments, the expected cost and time involved in its implementation will be lower. Thus, AI can be more easily adopted. This leads to the following hypothesis.

H1a. Compatibility is positively related to AI adoption.

Relative advantage

Relative advantage is the degree to which an innovation is perceived as being better than the approach it supersedes (Yang et al., 2013). Rogers (2003) notes that the perceived benefit of innovation affects an organization's intention to adopt innovative technology. Therefore, new technologies that have clear and unambiguous advantages in creating strategic and operational effectiveness are more likely to be adopted (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). In other words, the higher the perceived relative advantage of innovative technology is, the faster it will be adopted.

When facing severe market competition in a dramatically changing business environment, firms are prompted to adopt state-of-the-art information technologies to improve their business operations. AI has powerful computing capabilities, deep learning capabilities, and cross-border integration (Russell & Norvig, 2016). AI holds the promise of playing a major role in the

widespread promulgation of new services. The combination of AI technologies and massive data will inevitably bring innovation and competitive advantages to firms. To date, AI has been applied in customer service chatbots, speech and voice services for customers, and automatic network operation (El Khatib, Al-Nakeeb, & Ahmed, 2019). These applications lower firms' operation costs, increased their service quality, improved their customers' experiences, and promoted their efficiency. If a company instills awareness to its employees that how the core AI technologies such as NLP and deep learning can create efficiencies and reduce costs via education or training, employees can complete an understanding of the advantages that AI can offer. Once the level of awareness is raised, people may accept and actively participate in the positive changes provided by AI. This leads to the following hypothesis.

H1b. Relative advantage is positively related to AI adoption.

Complexity

Complexity is the extent to which the innovation is perceived as relatively difficult to understand and use (Yang et al., 2013). In other words, complexity means the obstacles or barriers to AI adoption. The easier it is to integrate the technology into business operations, the greater the chance of its adoption (Oliveira et al., 2014). The complexity of AI lies in the lack of maturity, the lack of technological expertise and IT specialists, time-consuming, and high cost. The characteristics of AI indicate that the largest obstacle for AI adoption is its immaturity. Previous studies find that the level of IT maturity significantly affects firms' strategic decisions in acquiring and deploying IT/IS. If a new technology is mature, firms know better about its implementation. If they know they can collaborate effectively with vendors, firms are more likely to adopt the new technology (Huang & Palvia, 2001).

Another obstacle for AI adoption is the lack of expertise in AI software and data analysis. Attewell (1992) points out that firms postpone in-house adoption of a complex technology until they have enough technical knowledge to implement and operate it successfully. At present, AI is still new to many firms who lack a full understanding of AI technologies. Given that AI technologies are still developing and changing, it is difficult to evaluate the return on investment of AI at this stage. Expensive and resource-intensive AI initiatives and pilot tests cannot guarantee the benefits they can bring. Thus, Gartner expects that firms need to spend about 3-5 years before obtaining reasonable benefits from AI. This leads to the following hypothesis.

H1c. Complexity is negatively related to AI adoption.

3.2 Organizational capability

Organizational capabilities include the resources of leadership, managerial capabilities, and technical capabilities that are available to support the adoption of an innovation. These capabilities are generally organization-specific, nontransferable, and embedded in an organization. The resource-based view (RBV) theory can be applied to identify organization-specific capabilities that contribute to AI adoption. RBV posits that firms create competitive advantage by combining available heterogeneous resources that are economically valuable, difficult to imitate, and nontransferable (Garrison et al., 2015; Wernerfelt, 1984). This means that organizations' unique and rare resources can yield short term advantages over competitors. Firms can improve their performance by adopting AI technologies. In this way, they can obtain advantages over their competitors. Thus, organization-specific capabilities differentiate firms from their competitors.

Managerial support

Commitment from managers is a critical factor in any major organizational change because it guides the allocation of resources and the integration of services (Co et al., 1998). Scholars find that managerial support is an important factor in IS implementation (Müller & Jugdev, 2012; Nah, Lau, & Kuang, 2001; Sanders & Courtney, 1985) and in IT adoption (Chong et al., 2009; Li, 2008; Teo et al., 2006; Thong, 1999). For example, Thong (1999) finds that the characteristics of senior executives in organizations affect their IT adoption. Hage and Dewar (1973) find that managers who are in the higher levels and have the power to allocate organizational resources influence the adoption of innovation. Elbanna (2013) argues that managerial support needs to be consistent and constant during project implementation, otherwise the project could fail. The reason is that managers, especially at the higher levels, can designate key personnel to oversee a certain project and allocate plenty of financial and other resources to the project (Willis & Sullivan, 1984). On the contrary, the lack of managerial support could impact a project negatively (Wixom & Watson, 2001).

AI technologies can bring organization-wide changes. Such changes can have a significant impact on firms. Given the important role of managers in IT adoption, AI applications need supports from managers and align with firms' strategic goals. When managers understand AI technologies and the work that the entire firm is involved in AI, they can determine how to use AI. In addition, once managers identify AI applications as top priorities, they tend to be more involved and willing to allocate resources for implementing these applications (Nah et al., 2001). It's also important that managers have a tangible and intuitive understanding of AI, which helps them maintain the most efficient relationship with their suppliers. This leads to the following hypothesis.

H2a. Managerial support is positively related to AI adoption.

Technical capability

Technical capability refers to the physical assets that are essential to adopt innovations, such as computer hardware, data, and networking (Aboelmaged, 2014). Meanwhile, it also represents the collective resources that a firm possesses for providing itself a flexible and scalable foundation for business applications (Wang, Chaudhry, & Li, 2016). Technical capability also includes intangible assets such as technical knowledge, IT development and collaboration strategies, and application processes that can effectively integrate new technologies (Garrison et al., 2015). It is a key factor that affects IT adoption (Garrison et al., 2015; Wu et al., 2007). Strong technical capability reduces the complexities of integration and allows the IT department to deliver AI technologies rapidly and efficiently. When a firm can deliver technical solutions effectively and integrate new AI technologies into its existing infrastructure efficiently, it can successfully adopt AI applications. The more capable the firm to integrate AI new technologies into the existing IT infrastructure, the faster the firm can reduce expenses and rationally allocate resources to achieve successful adoption. Whether a firm uses open source software or chooses vendors or partners to develop its own AI platform or tools, it must understand the technologies, skills, and resources needed to leverage AI's potential. This leads to the following hypothesis.

H2b. Technical capabilities are positively related to AI adoption.

Managerial capability

Managerial capability refers to the ability of managers to influence, motivate, and enable employees to contribute toward the effectiveness and success of the organization (House, Javidan, Hanges, & Dorfman, 2002). It includes decision making, creating a strong workplace and culture, achieving goals and objectives efficiently, and nurturing creativity and innovation. In the context

of IT, managerial capability includes project coordination as well as education and training. Managerial capability represents intangible assets that play a key role in IT adoption (Garrison et al.,2015). Tornatzky and Fleischer (1990) note that a firm is a source of architectures, processes, attitudes, and culture and that the source affects its IT adoption. Emmelhainz (1988) finds that the main factor hindering IT adoption is organizational resistance to change. Good managerial capabilities are reflected in having clear strategic goals and plans, efficient and smooth internal communication and cooperation, and education and training throughout the organization (Wixom & Watson, 2001).

AI presents an entirely new way to make sense out of the massive cloud of data. Therefore, an overall strategic vision and strategic plan of AI is the premise and guarantee for AI adoption. A lack of strategic plan and vision could impede IT innovations (Angeles, Corritore, Basu, & Nath, 2001; Armstrong & Sambamurthy, 1999). Undertaking an AI application also requires significant changes in business processes. In order to facilitate AI adoption, firms should have an excellent project management team, good internal communication and collaboration, and formal education and training. Some organizational inhibitors, such as lack of dedicated team (Grover, Jeong, Kettinger, & Teng, 1995), lack of communication among organizational members (Grover et al.,1995; Nakayama, 2003), and inadequate training (Angeles et al., 2001; Parker & Swatman, 1995), are found to hinder organizations' IT adoption. Firms with strong managerial capability can remove these barriers and adopt new technologies quickly.

Organizational management is in a dynamic environment with constant changes. An excellent management team can formulate appropriate marketing strategies, promote resource sharing, and improve organizational efficiency. The managerial capability allows firms to anticipate emerging technologies and leverage them effectively to coordinate business processes with their goals

(Garrison et al., 2015). Currently, AI applications are growing very fast. Many companies started to step into this field. For companies, it is easy to introduce and invest new AI technology, but it is difficult to let the existing organizational culture and processes adapt to AI. The successful adoption depends on the organizational managerial capability. Because although the innovation attributes of AI in a firm are objective, they are reflected in employees' perceptions, which can be changed by managerial capability. If the managers can realize the potential of AI new technology to improve the professional skills and practical value of employees, then adjust staffing and recruit corresponding technical professionals, rationally allocate resources, focus on training, and create conditions for adopting AI, the difficulty of AI application can be reduced. An excellent project management team, good internal communication and collaboration, and formal education and training in a firm can inspire employees' enthusiasm for learning, improve their ability to accept AI technologies, and reduce the potential risks. This will greatly reduce the conflicts and negative emotions of employees due to the difficulty and complexity of the process causing by AI technologies and applications. That means AI will be better compatible with the current processes and culture. The high level of managerial capability increases the perception of the new technology's usefulness and benefits (relative advantage and compatibility) and reduces the perception of technological risks (complexity). As a result, the firm can adopt AI technologies and applications fast, enhance its performance, and obtain competitive advantages. This leads to the following hypotheses.

Managerial capabilities significantly influence the innovation attributes of AI: positively related to the compatibility of AI (H3a); positively related to the relative advantage of AI (H3b); and negatively related to the complexity of AI (H3c).

Managerial capability can affect managerial support. In general, managers in an organization have three levels: top managers, middle managers, and first-line managers (Floyd & Lane, 2000). Different managers focus on different aspects of the business within the organization, from strategy to communication to operation. A company's management team consists of these three levels of managers. Managerial capability means the ability of these managers to build and configure resources to achieve organizational goals (Adner & Helfat,2003). The modern enterprise is a large and intricate system, and the management team often does most management and decision-making work. Strong managerial capability indicates an efficient management team. Managerial capability is important for a company. Kor and Mesko (2013) point out that managerial capability can influence the managers' dominant logic. Therefore, as time goes on, the manager's dominant logic expands and embeds company-level practices, procedures, and resources to form the dominant logic at the company level, and potentially changes the way companies make decisions and operations (Kor & Mesko, 2013; Laitila, 2018). A company with an efficient management team often has efficient communication and cooperation mechanisms, targeted training programs and processes, and continuous competitive advantage. Therefore, the stronger the company's managerial capability and the more efficient the management team, the more recognized and supported by the company's top manages. No chief executive officer likes an inefficient management team. Proposals and plans made by a powerful and effective management team will be easier to get managerial support. Therefore,

H3d. Managerial capabilities are positively related to managerial support.

In addition, managerial capability also influences technical capability. Technical capability includes not only physical assets such as hardware, software, and networking but also intangible assets such as technical knowledge and problem-solving processes. Kettinger, Davis, and

Kettinger (2015) point out that the technical capability of an organization is a collection of hardware, software, shared services, management practices, and technical skills. The physical assets of IT capability have no significant effect on the acquisition of competitive advantage. This is because they are relatively easy to obtain for competing companies. Once a company introduces a new technology or system, its competitors will follow, thus eliminating the original competitive advantage. While the intangible assets of IT capability are a unique, scarce, non-replicable, and valuable organizational resource. These capabilities are the knowledge, skills, abilities, and attitudes that managers need to configure IT-related resources to integrate new technologies effectively. So, the intangible assets of IT capability can be considered as a specific type of managerial capability. Managerial capability includes the skills of coordination and leadership that can facilitate new technology innovation (Bharadwaj, 2000). Strong managerial capability can influence organizational culture, improve the overall quality of employees, enhance the efficiency of internal and external communication, facilitate the delivery of technical solutions for integrating AI technologies, and achieve firms' goals. An efficient management team with strategic vision can create an energetic environment, rationally allocate resources, find and hire experienced IT managerial and technical talents, create conditions for technological innovation, and thus enhance the overall technical capabilities of the organization. This leads to the following hypotheses.

H3e. Managerial capabilities are positively related to technical capabilities.

3.3 External environment

As an arena that firms conduct their business, the external environment includes the industry, competitors, regulations, and interactions with the government (Chau & Tam, 1997). The institutional theory highlights the importance of institutional environments in shaping organizational structure and actions (Scott, 2008). Gibbs and Kraemer (2004) also note that firms

are influenced by their external environment. Therefore, organizational decisions are driven not only by rational goals of efficiency but also by social and cultural factors as well as concerns for legitimacy. The external environment can create incentives and barriers for firms to adopt new technologies. Firms are likely to adopt and use AI by external isomorphic pressures from government, competitors, and customers (Gibbs & Kraemer,2004).

Government involvement

Government policy plays an important role in stimulating IT innovation (Mogel, 2003; Lemke, 2003). Huang and Palvia (2001) find that the government can encourage IT diffusion and that regulations can set or remove barriers to introduce new IT or systems. The government could establish supportive plans and policies to promote the commercial applications of new technologies and create new rules for the development of new technologies. Stoica, Miller, and Stotlar (2005) point out that the adoption of new technology is a complex process, and the framework set by the government is important. As a disruptive technology with a wide range of influences, AI involves many issues such as security, privacy, and social ethics. Thus, AI needs well legislation or regulatory environment. That means while the rapid development of AI technology, the challenges and conflicts brought by law, security, employment, ethics, and government governance are increasing. Therefore, the overall planning and AI legislation at the national level can promote the benign development of the AI industry. In addition, because AI is transforming almost every facet of human life and society, governments around the world have dedicated substantial resources to investing in the technology and released national-level AI development plans and policies (Beckett & Ge, 2017; Creemers, 2017; Dutton, 2018; Hall & Pesenti, 2017; ITI, 2017; Markram, 2012; NITRD, 2016). The supports from the government provide a favorable environment for AI and will promote the diffusion and consequences of AI

(Agrawal, Gans, & Goldfarb, 2018). AI providers need to maintain a good relationship with the government for obtaining supports and resources to promote new AI applications. This leads to the following hypothesis.

H4a. Government involvement is positively related to AI adoption.

Competitive pressure

Competitive pressure is a driving force for technology innovation. Adopting new technology is often a strategic necessity to compete in the marketplace (Lippert & Govindarajulu, 2006; Sumner, 2000). Firms' competitive advantages are not fixed and long-lasting, but temporary. Porter and Millar (1985) point out that IT innovation can change industry structure, alter the rules of competition, leverage new ways to outperform rivals and change the competitive environment. Mansfield et al. (1977) find that fierce market competition stimulates the rapid diffusion of IT innovations. Pressure from competitors is an important factor in IT adoption (Gibbs & Kraemer, 2004; Kuan & Chau, 2001). Adopting new technologies is often a necessary strategy for firms to compete in the marketplace. Firms feel pressure if their competitors adopt certain new technologies. They tend to adopt these technologies immediately to maintain their competitiveness (Oliveira & Martins, 2008). Firms that successfully apply new AI technologies to improve their products and services will gain competitive advantages over their competitors. Therefore, competitive pressure drives firms to adopt AI technologies and applications. This leads to the following hypothesis.

H4b. Competitive pressure is positively related to AI adoption.

Market uncertainty

Market factors, such as the demand for products, the degree of competition in the market, and the degree of loyalty of customers, are out of firms' control but can affect their performance (Hao,

Padman, Sun, & Telang, 2018). As we all know, there are so many uncertainties in any commercial market. Risk and opportunity coexist. Whoever can find certain opportunities under uncertain market will gain competitive advantages. Many countries and organizations have released AI development plans or related regulations to capture the opportunities created by AI. China pointed out in the New Generation Artificial Intelligence Development Plan that by 2030, China's AI core industry will exceed 1 trillion yuan, driving the relevant industries to exceed 10 trillion yuan, which indicates that AI provides an extensive market and huge opportunity (Creemers, 2017). Currently, many AI technologies and applications are still immature, and there is a shortage of relevant professional and technical personnel, but AI has already shown strong vitality and provides companies with more competitive opportunities. For example, customer service chatbots and voice assistants can help firms increase efficiency and reduce labor costs. The chatbot TOBi released by Vodafone has already handled more than 70% of customer queries (Vodafone, 2017). In addition, some complex tasks such as fingerprint recognition and fact detection only can be handled by AI technologies. Firms can apply AI technologies to increase their existing customers' loyalty and attract new customers. AI applications have huge market potential, but the current application scenario of AI remains to be explored. Although many applications are still in the development and testing phase, this cannot prevent smart companies from stepping into the AI field. This leads to the following hypothesis.

H4c. Market uncertainty is positively related to AI adoption.

Vendor partnership

In general, a firm does not have all the technical and transformational skills in-house for managing innovations, such as AI. Thus, AI adoption in firms is usually associated with IT vendors and collaborative partners because many firms are unfamiliar with AI technologies. Assael (1984)

finds that vendor involvement can significantly contribute to the rate of adoption and diffusion of new products. Vendor partnership has been empirically supported as one of the critical determines for innovation adoption (Ahmadi, Nilashi, Ibrahim, Ramayah, Wong, Alizadeh, & Almaee, 2015; Sulaiman, & Wickramasinghe, 2014; Yang & Kankanhalli, 2013). Currently, many firms purchase the vast majority of IT and network technologies from standards-compliant vendors. But these vendors are not the best source of AI technologies. Suppliers play a unique and significant role in the AI field. Vendors need a huge amount of data to train their AI tools, which often contain sensitive customer information. Therefore, vendors often can't sell plug-and-play applications of AI; they need to work closely with companies (their customers) to perform AI training during and after the deployment. In order to cooperate with leading AI technology vendors, firms must standardize the data collection and management process to make it easier to use AI technologies. In addition, algorithms and models are the core elements of AI. Because many firms are not good at algorithms, they need to build a platform open to vendors for developing AI applications jointly. Therefore, vendor partnerships can greatly influence the process of AI adoption. For example, China Unicom cooperates with Baidu, Iflytek, Alibaba, Tencent (all of them are high technology companies) to develop AI applications such as smart products and intelligent services. AT&T and Tech Mahindra jointly develop an open-source AI platform. Nokia and China Mobile established a joint AI/5G lab to research AI applications in 5G networks. This kind of cooperation has fully utilized the helpful resources in their respective fields and jointly promoted the application of AI in the form of resource replacement and complementary technologies. Therefore, AI vendors can promote AI applications to a large extent. This leads to the following hypothesis.

H4d. Vendor partnership is positively related to AI adoption.

4. METHODOLOGY

4.1 Measures

The primary research instrument for this study is a questionnaire designed to collect data on AI adoption. The framework has 11 latent factors, namely government involvement, market uncertainty, competitive pressure, vendor partnership, managerial capability, managerial support, technical capability, compatibility, relative advantage, complexity, and AI adoption. The questionnaire is developed by adapting items from previous studies on innovation, diffusion, implementation, and adoption of information technology. Some items are modified to reflect the unique characteristics of AI. A 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree), is applied to measure the items.

Government involvement adapted from Chang et al. (2006), Oliveira et al. (2014), and Yang et al. (2013) was operationalized by asking respondents to determine (1) the government policies are beneficial for their business; (2) the government provides financial aid; (3) the government supplies information; (4) maintain relationship with government;(5)The government support is important for innovating. The first two items were deleted during the factor analysis process due to their low factor loadings. Moreover, in China, telecom operators are state-owned large companies. The regulatory environment is different from other countries. In addition to commercial market competition, they also must take social responsibility, such as ensuring nationwide communication coverage. The national speed-up and fee-reduction policy actually require operators to reduce profit margins while improving service quality. Therefore, for these operators, government policies are not beneficial for their business.

Market uncertainty derived from Chau and Tam (1997) was measured by asking respondents to opine on (1) your industry trends to utilize AI technologies; (2) AI has broad application prospects in your industry; (3) only innovative technologies can help your company to meet the growing needs of customers; (4) your company can gain competitiveness via AI. The third item was dropped during the factor analysis process because it had a high covariance residual. In addition, customer needs are increasingly diverse and personalized. For operators, innovative technology is the best way to provide new products to attract customers and satisfy their growing needs. But operators can also increase their customer satisfaction by improving customer service quality. Telecom operators have focused on differentiation in online services, offline business hall services, and personalized customer service to enhance user experience and competitiveness. So, the third item was eventually deleted.

Competitive pressure adapted from Chang et al.(2006) was operationalized including (1) the rate of innovation in your industry increases dramatically;(2)your industry utilizes AI technologies will put pressure on your company;(3) your industry shows tough price competition; (4) your industry shows tough competition on product and service quality. The second item was deleted during the factor analysis process because of the low factor loading. In addition, the homogenization competition in the telecom industry is very fierce. If one operator launches a new product or a new package, other operators will follow up with a similar product or package to compete with it. AI technologies can help operators improve network management efficiency, enhance service quality and customer experience, and increase competitiveness. Therefore, regardless of whether other operators have begun to apply AI, operators will consider adopting AI technologies or applications because AI is too important for their sustainable development.

Vendor partnership adapted from Han, Lee, and Seo (2008) and Zhu et al. (2003) was measured with five items that describe the role of vendors. The five items include (1) vendors provide assistance or reliable services; (2) vendors are trustworthy; (3) vendors make decisions beneficial to your company; (4) your company's relationship with vendors is close; (5) vendors are knowledgeable for AI technologies. The fifth item was deleted during the factor analysis process because of the low factor loading. What's more, unlike other applications, AI applications need powerful technical support. For example, China Mobile and Microsoft cooperated to develop AI speech recognition application, China telecom selected Nokia Bell to promote the application of AI in mobile communication networks, China Unicom cooperated with Baidu to release an AI assistant called Xiaodu1C, China Tower chose Alibaba as its strategy to develop AI applications. Vendors such as Microsoft, Nokia Bell, Baidu, and Alibaba, are all high-tech companies and experts in the field of AI. As AI vendors, knowledgeable for AI technologies is a necessary condition for them. Therefore, the fifth item didn't need to exist.

Managerial capability adapted from Ravichandran and Lertwongsatien (2005) and Garrison et al. (2015) includes five items: (1) your company has clear goals and objectives to adopt AI; (2) your company has great project management team for AI adoption; (3) the inter-department cooperation is very important to AI adoption; (4) the inter-department communication is very important to AI adoption; (5) your company can provide formal education and training to all classes of users. The first two items were dropped during the factor analysis process because of their lower factor loadings. In addition, because AI is still in the early stages of adoption. There are not many mature commercial applications of AI. Many companies are still considering or planning AI. Therefore, so far, they have no clear goals and a specific project management team for AI adoption.

Managerial support adapted from Garrison et al. (2015) and Han et al. (2008) was operationalized with five items that describe the degree of managers' support. The five items used for the measures were (1) the managers in your company demonstrate to support the AI adoption; (2) managers are willing to take risks involved in AI adoption; (3) the ability of managers to exploit new technologies; (4) the ability of managers to leverage new technologies; (5) the managers can understand to increase business performance via AI technologies. The first item was deleted because it has a lower factor loading. In addition, like the fifth item of vendor partnership, the first item is a necessary condition. Managerial support for AI adoption reflects in the willing and ability of managers that can support and ensure the company to adopt AI. The first item is an outline narrative, not a specific support item.

Technical capability adapted from Garrison et al. (2015) and Han et al. (2008) was measured by four items which demonstrate the technical capability the organization should have for innovation adoption: (1) standardized process for innovation; (2) quickly integrate AI technologies into current IT infrastructure;(3) IT strategies support business strategies; (4) the ability to protect the security and privacy of systems and networks. The second item was dropped during the factor analysis process because it existed cross-loading. Furthermore, unlike other technologies and systems, many AI technologies are disruptive. In order to apply AI technology, companies may change their IT infrastructure instead of integrating the current IT infrastructure. For example, Huawei released SoftCOM AI, which integrates AI technology into the cloud-based architecture and solutions and creates self-driving network architecture to help operators create automated networks that never fail. Therefore, the second item was unsuitable for AI adoption.

Compatibility was derived from Chang et al. (2006), Chong et al. (2009), and Thong (1999). It was operationalized with five items that measure how AI application is compatible with the

organizational IT environment. The five items were (1) AI is compatible with the communication/network environment;(2) AI is compatible with software environment; (3) AI is compatible with hardware environment; (4) AI is compatible with infrastructure; (5) AI is compatible with data resources. The second item was dropped during the factor analysis process because of the low factor loading.

Relative advantage adapted from Chong et al. (2009) and Thong (1999) was measured by five items that describe the potential benefits of adopting AI. The five items used for the measures were (1) AI can increase revenues and profitability; (2) AI can get higher employee productivity; (3) AI can improve customer service; (4) AI can better utilize IT resources; (5) AI can promote flexibility and integration. The first item was deleted because it has a lower factor loading. In addition, although AI applications are showing flourishing, AI is still in the early stage of adoption. The expensive and resource-intensive AI programs and pilot tests cannot guarantee the benefits they bring. Therefore, AI cannot increase revenue and profitability currently, and then the first item was dropped.

Complexity adapted from Chong et al. (2009) and Thong (1999) was operationalized with four items which list the potential risks of adoption AI. The four items include (1) AI lacks application maturity; (2) The application and migration of AI cost a lot; (3) AI adoption is time-consuming; (4) inappropriate staffing and personnel shortfalls.

AI adoption was measured by asking respondents to give their opinion on the following five statements of adoption AI which can indicate the degree of AI adoption: (1) a timely AI plan has been developed; (2) the plan has been endorsed by managers; (3) a financial budget and migration schedule have been approved;(4) customers highly accept new products and services using AI innovations; (5) AI innovation has improved the competitive position. These items were adapted

from Chau and Tam (1997) and Reich and Benbasat (1990). The fifth item was dropped during the process of factor analysis due to its lower factor loading. Moreover, the application of AI in the field of communication is still in its infancy, and AI technologies may have the potential capability to help operators to increase competitiveness. So far, there are no successful adoption cases that can prove this yet. Therefore, the fifth item was dropped because it was not suitable for AI adoption.

These items are then incorporated into a final survey instrument with 60 questions. The factors and questions in the survey are shown in Table 3. Because the questionnaire is administered in China, the English version of the instrument is translated into Chinese and reviewed by several IS researchers and language experts. Then the Chinese version instrument is back translated into English to confirm translation equivalence (Brislin, 1970).

A pilot study with 68 samples is conducted among representatives of IT managers in the Chinese telecom industry to test the overall quality of the instrument. In specific, the pilot study assesses the consistency, ease of understanding, and appropriateness of the questions in the questionnaire. The results of the pilot study provide evidence that the scales are reliable, valid, and have translation equivalence (Brislin,1970). The screening process does not show any major functional issues with the survey instrument. Based on the feedback in the pilot study, formatting and presentation improvements of some questions are made. Pilot data is not merged with data collected in the main study for avoiding possible contamination.

Table 3. The Description of Constructs and Items

Construct	Source/Items
Government involvement	(Chang et al. ,2006; Oliveira et al., 2014; Yang et al., 2013)
	The specification and stability of government policies are beneficial for business operation. (Deleted)

	The government provides financial aid (Deleted)
	The government supplies related information
	We should maintain good relationship with local government.
	The government support and help are very important for us to innovate
Market uncertainty	(Chau & Tam, 1997)
	There is a trend in our principal industry to utilize more AI technologies for business development and applications.
	AI has broad application prospects in our principal industry.
	Only innovative technologies can help our company to provide perfect products and services to meet the growing personalized needs of consumers. (Deleted)
	AI can help our company to gain competitiveness.
Competitive pressure	(Chang et al., 2006)
	The rate of innovation of new operating processes and new products or services in our principal industry has increased dramatically.
	An industry moves to utilize the AI technologies for innovation would put pressure on our company to do the same. (Deleted)
	Tough price competition in our industry
	Tough competition on product/service quality
Vendor partnership	(Han et al, 2008; Zhu et al., 2003)
	We have had no difficulty in obtaining assistance or reliable services from our vendors/partners.
	Our vendors/partners are trustworthy.
	Vendor makes decisions beneficial to my organization.
	We have very close relationships with vendors/partners.
	Our vendors/partners are knowledgeable for AI technologies. (Deleted)
Managerial capability	(Garrison et al., 2015; Ravichandran & Lertwongsatien, 2005)
	We have clear goals and objectives to adopt AI technologies innovation. (Deleted)
	We have great project management team. (Deleted)
	The inter-department cooperation is very important to adopt AI technologies innovation.
	The inter-department communication is very important to adopt AI technologies innovation.
	Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers.
Managerial support	(Garrison et al., 2015; Han et al., 2008)
	The managers explicitly demonstrate to support the adoption of AI. (Deleted)
	Managers are willing to take risks involved in the adoption of AI.
	Our managers have the ability to exploit new technologies before our competitors.
	Our managers have the ability to leverage IT new technologies as a strategic core competence
	Our managers have a strong understanding of how AI technology can be used to increase business performance.
Technical capability	(Garrison et al., 2015; Han et al., 2008)
	We have standardized process for IT innovation.
	We have the ability to quickly integrate new AI technologies into our existing infrastructure. (Deleted)
	Our IT strategies support our business strategies
	We have suitable hardware/software to protect the security and privacy of our systems and networks.
Compatibility	(Chang et al., 2006; Chong et al., 2009; Thong, 1999)
	AI application is compatible with our current communication/network environment.
	AI application is compatible with our current software environment. (Deleted)
	AI application is compatible with our current hardware environment.
	AI application is compatible with our infrastructure.
	AI application is compatible with computerized data resources.
Relative advantage	(Chong et al., 2009; Thong, 1999)
	AI application can increase revenues and profitability. (Deleted)
	AI application can get higher employee productivity.
	AI application can improve customer service.
	AI application can better utilize IT resources.
	AI application can promote flexibility and integration.
Complexity	(Chong et al., 2009; Thong, 1999)
	Adopting AI innovation lacks application maturity.
	There has been a high cost for AI application and migration.
	Adopting AI innovation is time consuming.
	Inappropriate staffing and personnel shortfalls are a big issue for adopting AI innovation.
AI adoption	(Chau & Tam,1997; Reich & Benbasat,1990)
	A timely AI technical implementation and application migration plan has been developed
	The plan has already been endorsed by managers.
	A financial budget and a migration schedule have been approved.
	Our customers highly accept new products and services using AI innovations.
	We get improvement in the competitive position after adopting AI innovation. (Deleted)

Three control variables are measured in this study. They are firm size, annual sales, and enterprise affiliation. Following Garrison et al. (2015), this study assesses firm size using an ordinal scale based on the number of employees in a firm (1 means less than 500 employees; 2 means 500-999 employees; 3 means 1000-1499 employees; 4 means 1500-1999 employees; 5 means 2000-2499 employees; and 6 means more than 2500 employees). Literature indicates that firm size influences IT adoption. Large firms have more resources and can take greater risks associated with innovation adoption than small firms (Thiesse, Staake, Schmitt, & Fleisch, 2011). Annual sales are measured by an ordinal scale (1 means less than 5 million dollars; 2 means 5-10 million dollars; 3 means 10-50 million dollars; 4 means 50-100 million dollars; 5 means100 million-1billion dollars; and 6 means over 1 billion dollars). Affiliation may play a role in the AI adoption process. Enterprise affiliation is measured by an ordinal scale (1 means the headquarter; 2 means the provincial level; 3 means the municipal level, and 4 means the county level). The control of firm size, annual sales, and enterprise affiliation can minimize the variance in the decision of AI adoption caused by these variables.

4.2 Ethical Considerations

Permission to conduct this study is obtained from the Old Dominion University Business Human Subjects Review Committee (see Appendix A). This study follows the Institutional Review Board (IRB) criteria to collect data. The instruction of this survey notifies participants the purpose of the study, the nature of the study, school name, research name, email, the estimated time to complete this survey, the degree of risk (if any), and any obligations associated with the study. Participants are also notified that no sensitive or confidential information is required and that participation in

this survey is entirely voluntary. In addition, participants are guaranteed confidentiality and anonymity.

4.3 Sample

The target population for this study is managers and engineers from major Chinese telecom companies, including China Mobile, China Unicom, China Telecom, and China Tower. Telecom companies are chosen because they are the leader in the AI field. First, the telecom operator is the necessary user of AI technology, and the next-generation network is inseparable from intelligence. Second, the operator is the core driver of the AI industry, and the future intelligent era is inseparable from 5G and the Internet of Things. Third, the operator is the provider of AI services, open-source AI frameworks and generic AI application platforms may well become the norm in telecoms. That means telecom operators need AI technologies urgently to manage and maintain their complex network, to improve customer experience, and to promote efficiency. In addition, telecom operators are responsible for delivering the infrastructure. They can integrate 5G networks and AI to provide vertical industry applications and to expand their revenue. Therefore, telecom operators have a high desire to adopt AI.

Given the characteristics of the target population, a web-based survey is a suitable approach to collect data. It is more accessible, easy to complete, and less time consuming for the respondent. The researchers can benefit from faster response rates and easier data collection and analysis due to automatic coding (Kiernan, Kiernan, Oyler, & Gilles, 2005). KwikSurveys is chosen for deploying the online survey instrument. The researchers choose social media and email to recruit participants. In the questionnaire, a clear description of AI and some examples of AI applications are provided for participants to understand AI better. According to Hair, Black, Babin, Anderson, and Tatham (1998), the minimum sample size should be five times larger than the total indicators

of measurement scale in quantitative research. Because the initial research model in this study has 51 observed indicators representing 11 latent constructs, the minimum sample size should be 51 * 5 = 255.

The online survey began on February 10 and ended on March 10 for about a month which receives 346 responses initially. The collected data is screened for missing values, suspicious response patterns, and outliers (Hair, Hult, Ringle, & Sarstedt, 2014). After the screen, the valid responses drop to 289. Factors analysis is performed on the research model, and the revised measurement model has 39 observed indicators. The required minimum sample size changes to 39*5=195. Therefore, 289 responses meet the requirement to run the revised research model.

The profile of the sample is shown in Table 4. Among the participants, 7% are general or senior managers, 47% are middle managers, and 29% are IT engineers. Regarding enterprise affiliation, 71% of participants are at the municipal level, followed by headquarter (12%) and provincial level (10%). Fifty-four percent of participants are from China Unicom, 22% from China Tower, 15% from China Mobile, and 6% from China Telecom.

Table 4. Respondent Demographics

Demographic categories	Frequency	Percentage
Current position		
General manager	9	3.11
Senior manager	12	4.15
middle manager	137	47.40
IT engineer	85	29.41
Others	46	15.92
Number of full-time employees		
Less than 500	80	27.68
500-999	19	6.57
1000-1400	21	7.27
1500-1999	24	8.30
2000-2499	27	9.34
Over 2500	118	40.83
Annual sales for most recent year		
Less than 5 million	31	10.73

5-10 million	21	7.27
10-50 million	28	9.69
50 million -100 million	24	8.30
100 million -1 billion	90	31.14
over 1 billion	95	32.87
Enterprise affiliation		
Headquarter	35	12.11
Provincial level	30	10.38
Municipal level	206	71.28
County level	18	6.23
Name of company		
China Mobile	44	15.22
China Telecom	18	6.23
China Unicom	155	53.63
China Tower	63	21.80
Others	9	3.11

4.4 Data analysis and results

This study uses structural equation modeling (SEM) to analyze sample data and evaluate model fit. SEM is a second-generation multivariate data analysis technique for high-quality statistical analysis (Chin, Marcolin, & Newsted, 2003). SEM is performed in Analysis of Moment Structures (AMOS), a covariance-based SEM technique that is well suited for the analysis of models containing variables with measurement error (Gefen, Straub, & Boudreau, 2000). The study combines multivariate analysis with regression analysis to examine factor analysis and concept relationships. In this study, the measurement model and structural model are analyzed in SPSS Amos 25.0.0. The measurement model shows the relations between the constructs (latent variables) and their indicators (observed variables), whereas the structural model shows the potential causal dependencies between the latent variables (Chin et al., 2003).

4.4.1 The measurement model

The adequacy of the measurement model is assessed by checking the reliability of individual items, construct validity, convergent validity, and discriminant validity of the measurement instrument.

Eleven latent constructs (factors) and their observed variables (indicators) in the proposed model are measured.

First, factor analysis is conducted to identify and to confirm the indicators under each construct regarding success factors for AI adoption. Some indicators are dropped because their factor loadings are too small (<0.4) or they are part of crossing loadings. The KMO coefficient is 0.927 (> 0.5). The result of Bartlett's testing (Sig. =0.000) indicates that the factors analysis is suitable. Eleven factors are extracted from 39 observation variables. The variance extracted is 79.868% (> 50%). Table 3 shows the specific eliminated items. The results of confirmatory factor analysis (CFA) confirm that the significance of all paths between the remaining observed variables and the constructs is $p < 0.001$. According to Fornell and Larcker (1981), the construct validity of a model is explained through the percentage of extracted variance. The total variance explained by each indicator is in the range of 50%-85% (see Table 5), except for CP1, GI1, and VPP1% (49%, 48%, and 49% respectively).

Cronbach's alpha value of each construct is shown in Table 5. They are all larger than 0.7, the commonly acceptable threshold (Kline, 2013). Composite reliability (CR) measures the internal consistency of the scales. It is a more rigorous estimate for reliability (Chin & Gopal, 1995). The recommended value of CR for establishing acceptable model reliability is 0.7 (Gefen et al., 2000). The values of CR for each construct are all larger than the threshold. Therefore, the construct reliability of the model is established.

Convergent validity assesses consistency across multiple items. It is measured by the Average Variance Extracted (AVE). Table 6 shows the AVE values of all constructs. They are all larger than the recommended threshold of 0.50 (Fornell &Larcker, 1981). This means that at least 50% of measurement variance of the indicators on average is captured by the latent constructs (Chin,

1998). In addition, all estimated standard loadings are significant at $p < 0.001$, higher than the acceptable magnitude of 0.50 (Chin & Marcolin, 1995). Thus, the measurements in the model have good convergent validity.

The discriminant validity of constructs is assessed with Fornell–Larcker criterion, which postulates that the square root of AVE should be higher than the correlations between the constructs (Fornell & Larcker, 1981). As shown in Table 6, the square root of the AVE of each latent construct, bolded on the diagonal, is higher than the inter-construct correlations in the corresponding columns and rows. Therefore, the discriminant validity of constructs is established. In addition, the interitem correlations are all below the threshold 0.90 (Bagozzi, Yi, & Phillips, 1991), indicating the distinctness of each construct.

Although some constructs are marginally low in construct validity, most constructs exhibit acceptable validity and reliability. Hence, the validity and reliability of the constructs in the model are established.

Multicollinearity occurs when high correlations exist among predictor variables, causing unreliable and unstable estimates of regression coefficients. Variance inflation factor (VIF), defined as the degree to which the standard error is increased due to the presence of collinearity, is applied to diagnose multicollinearity. Examining the correlation table for evidence of multicollinearity among the eleven latent constructs (Table 6) shows that all VIF values are below the threshold 5.0 (Kline, 1998). The range of VIF values is from 1.175 to 2.702. This suggests that there is no multicollinearity among predictor variables.

Table 5. Items and Descriptive Statistics

Item	Cronbach Alpha	Total variance explained R^2	Loading (Std. Regression Weights)
AI adoption (AIA)	0.926		
AIA1		0.768	0.876***
AIA2		0.742	0.862***
AIA3		0.786	0.886***
AIA4		0.734	0.857***
Compatibility(C)	0.935		
C1		0.753	0.868***
C3		0.791	0.890***
C4		0.837	0.915***
C5		0.755	0.869***
Competitive pressure (CP)	0.830		
CP1		0.485	0.697***
CP3		0.591	0.769***
CP4		0.847	0.920***
Complexity (CX)	0.928		
CX1		0.744	0.863***
CX2		0.839	0.916***
CX3		0.733	0.856***
CX4		0.749	0.865***
Government involvement (GI)	0.808		
GI3		0.475	0.689***
GI4		0.681	0.825***
GI5		0.622	0.789***
Managerial capability (MC)	0.900		
MC3		0.750	0.866***
MC4		0.812	0.901***
MC5		0.696	0.834***
Market uncertainty (MU)	0.831		
MU1		0.544	0.737***
MU2		0.802	0.896***
MU4		0.553	0.744***
Relative advantage (RA)	0.869		
RA2		0.549	0.741***
RA3		0.548	0.740***
RA4		0.695	0.834***
RA5		0.725	0.851***
Technical capability (TC)	0.875		
TC1		0.708	0.841***
TC3		0.680	0.825***
TC4		0.716	0.846***
Managerial support (MS)	0.892		
MS2		0.602	0.776***
MS3		0.735	0.857***
MS4		0.689	0.830***
MS5		0.682	0.826***
Vendor partnership (VPP)	0.903		
VPP1		0.493	0.702***
VPP2		0.786	0.887***
VPP3		0.753	0.868***
VPP4		0.787	0.887***

Note: *** is significant at the $p < 0.001$.

Table 6. Construct Correlations, Consistency, and Reliability

Construct	Composite reliability (CR)	Variance inflation factor (VIF)	Average Variance Extracted (AVE)	AIA	C	CP	CX	GI	MC	MU	RA	TC	MS	VPP
AI adoption (AIA)	0.926		0.757	**0.870**										
Compatibility (C)	0.936	2.702	0.784	.720**	**0.886**									
Competitive pressure (CP)	0.841	1.840	0.641	.311**	.323**	**0.801**								
Complexity (CX)	0.929	1.175	0.766	-.441**	-.329**	-0.108	**0.875**							
Government involvement (GI)	0.813	1.446	0.593	.192**	.289**	.442**	0.018	**0.770**						
Managerial capability (MC)	0.901	2.193	0.752	.512**	.571**	.535**	-.211**	.379**	**0.867**					
Market uncertainty (MU)	0.837	1.622	0.633	.259**	.258**	.545**	-0.070	.463**	.411**	**0.796**				
Relative advantage (RA)	0.871	2.105	0.629	.541**	.590**	.504**	-.144*	.404**	.591**	.443**	**0.793**			
Technical capability (TC)	0.876	2.305	0.701	.576**	.669**	.390**	-.281**	.270**	.585**	.296**	.544**	**0.837**		
Managerial support (MS)	0.852	2.466	0.677	.644**	.688**	.312**	-.264**	.283**	.547**	.286**	.519**	.654**	**0.823**	
Vendor partnership (VPP)	0.904	1.755	0.705	.554**	.568**	.240**	-.285**	.208**	.476**	.213**	.379**	.501**	.601**	**0.840**

Note: Bold numbers on the diagonal are the square root of the AVE.
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Based on the results of factor analysis, the proposed model's global measures of fit are assessed with the maximum likelihood method in AMOS. The fit indices chosen for the proposed model represent two characteristics: the global fit measures and comparative fit measures. The chi-square test ($\chi 2$) with degrees of freedom is chosen for checking the global model fit. The chi-square statistic must, however, be interpreted with caution especially for a large sample size because the hypothesized model may be rejected if the discrepancy is not statistically equal to zero. Therefore, comparative fit measures, including comparative fit index (CFI) and root mean square error of approximation (RMSEA), are selected to assess the congruence between the hypothesized model and the data because generally they are not affected by the sample size.

There are 11 latent constructs (factors) and 51 observed indicators in the initial model. Some indicators are dropped due to their lower factor loadings, higher residual covariances, and higher correlations with other indicators. The revised model has 11 latent constructs(factors) and 39 observed indicators. The final measurement model (CFA model) is shown in Figure 9. The results indicate that the loading weights of all observed variables are greater than 0.5 at the significant level of p=0. The fit statistics for the initial and final measurement model are listed in Table 7. The final measurement model has better fit statistics. The value of $\chi 2$ for the final measurement model is 1112 (DF=647). The ratio of $\chi 2$ and the degrees of freedom (DF) is 1.72, smaller than 3 (Hair et al., 1998), indicating a good fit. In addition, CFI is 0.95, and RMSEA is 0.05. They are both at the desired levels (Bagozzi & Yi, 1988; Hair et al.,1998). Overall, the final measurement model has good global measures of fit.

Table 7. Fit Statistics for Measurement Model

Model goodness of fit statistics	Initial Model	Final Model	Desired Levels (N>250, m>=30) (Hair, Black, Babin, Anderson, & Tatham,1998)
χ^2	2391.116	1111.812	Significant p-values expected
df	1169	647	-
χ^2/DF	2.045	1.718	<3.0
RMSEA	0.060	0.050	<0.07
CFI	0.894	0.947	>.90

Note: m=number of observed variables. N applies to the number of observations(samples).
RMSEA: Root mean square error of approximation; CFI: Comparative fit index

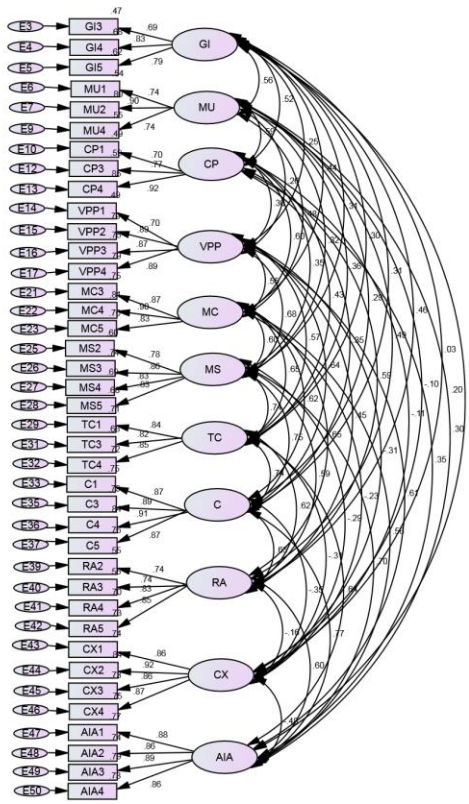

Figure 9. The Final Measurement Model (CFA model)

4.4.2 The structural model

4.4.2.1 The main study

The assessment of the structural model tests the suitability of the model and the research hypotheses. The goodness of fit indices for the structural model is displayed in Table 8. The value of χ^2 for the structural model is 1312. The ratio of χ^2 and the DF is 1.94. CFI is 0.927. RMSEA is 0.057. All the values meet the generally accepted threshold for satisfactory, indicating the good fit of the structural model.

The proposed relationships are supported if the corresponding path coefficients have the proposed sign and are significant. Therefore, the path coefficients are estimated to test the strength of the relationships between the independent and dependent variables, as well as R^2 value, which shows

the amount of variance explained by the independent variables. The highest standardized path coefficient symbolizes the strongest effect of predictor (exogenous) latent variable towards the dependent (endogenous) latent variable (Hair et al., 2014). The path coefficients are indicated on the paths between two constructs, along with their direction. The results of the analysis are summarized in Table 9 and Figure 10.

All the standardized path coefficients are significant at the level of $p < 0.1$ or higher (Table 9) except the path (H2b) "Technical capability→ AI adoption", the path(H4b) "Market uncertainty→ AI adoption", and the path(H4c) " Competitive pressure→ AI adoption". Combining the findings of fit indices obtained in the structural equation model analysis, it can be reached the conclusion that the sample data, in general, support the conceptual model shown in Figure 8. In addition, the variables and constructs represented in the model explain the variance of a significant portion of the endogenous constructs. This result, as well as the statistical significance of the structural paths, supports 11 of the total of 14 hypotheses proposed based on the conceptual model presented in Figure 8.

Table 8. Fit Statistics for Structural Model

Model goodness of fit statistics	Model value
χ^2	1311.749
df	677
χ^2/DF	1.938
RMSEA	0.057
CFI	0.927

RMSEA：Root mean square error of approximation；CFI：Comparative fit index

Table 9. Summary of Hypotheses Test Result for the Structural Model.

	Paths	Standard path coefficient	p-value	Results
H1a	Compatibility→ AI adoption	0.416	***	Support
H1b	Relative advantage→ AI adoption	0.157	0.019**	Support
H1c	complexity→ AI adoption	-0.223	***	Support
H2a	Managerial support→ AI adoption	0.206	0.011**	Support
H2b	Technical capability→ AI adoption	-0.028	0.703	Not support
H3a	Managerial capability → Compatibility	0.803	***	Support
H3b	Managerial capability→ Relative advantage	0.758	***	Support
H3c	Managerial capability→ Complexity	-0.304	***	Support
H3d	Managerial capability→ Managerial support	0.803	***	Support
H3e	Managerial capability→ Technical capability	0.827	***	Support
H4a	Government involvement → AI adoption	0.107	0.051*	Support
H4b	Market uncertainty→ AI adoption	0.04	0.494	Not support
H4c	Competitive pressure→ AI adoption	0.036	0.519	Not support
H4d	Vendor partnership→ AI adoption	0.113	0.048**	support
Control variables	Firm size →AI adoption	0.064	0.146	
	Annual sales→ AI adoption	0.063	0.157	
	Enterprise affiliation→ AI adoption	0.009	0.822	

Note: *P<0.1, **P<0.05, *** p<0.01 (Mithas, Ramasubbu, & Sambamurthy, 2011; Pavlou, Liang, & Xue, 2007; Wang, Tai, & Grover, 2013)

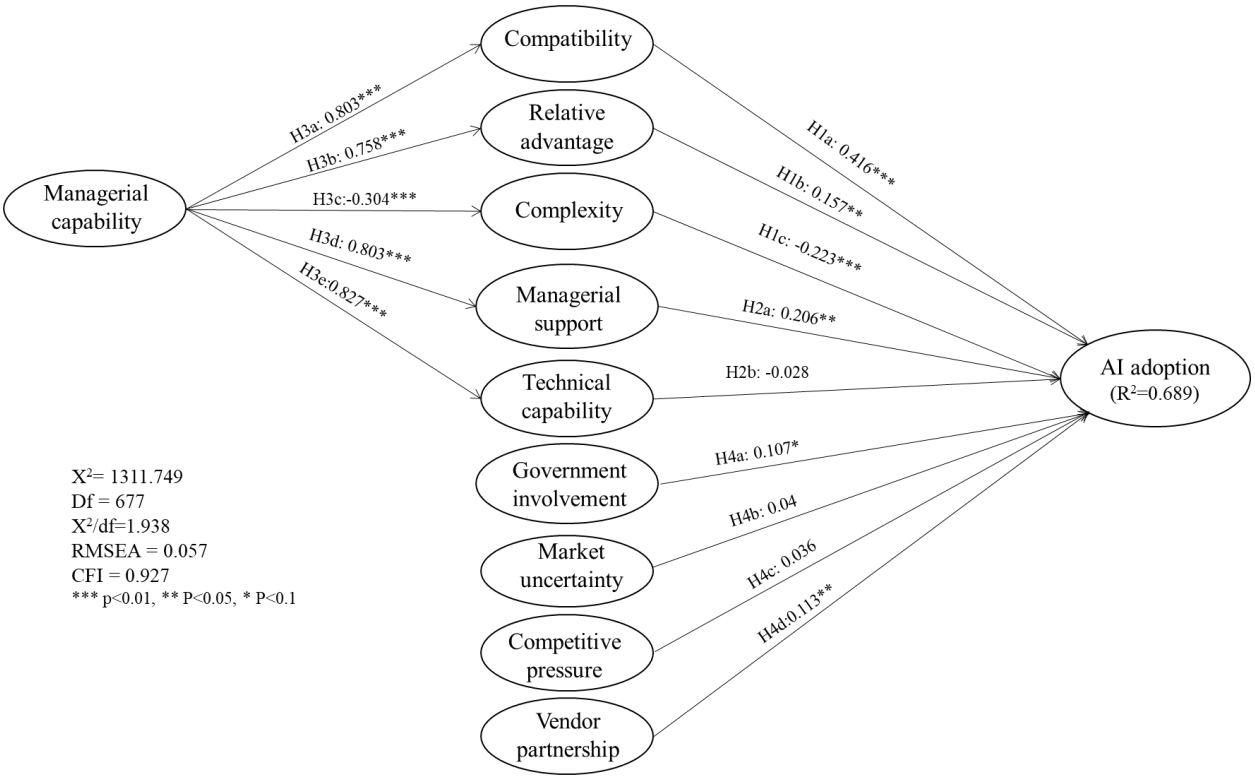

Figure 10. Structural Model

According to Chin (1998), R^2 is substantial with a value of 0.670, moderate with a value of 0.333, and weak with a value of 0.190. The value of R^2 is 68.9% in this research model. This indicates that the research model is significant in explaining AI adoption. H1a, H1b, and H1c are related to the innovation attributes of AI and they are all supported (H1a: $\beta = 0.416$, $p < 0.01$; H1b: $\beta = 0.157$, $p < 0.05$; H1c: $\beta = -0.223$, $p < 0.01$). This indicates that the innovation attributes of AI significantly affect AI adoption. Higher relative advantage, higher compatibility, and lower complexity of AI cause higher AI adoption.

H2a is supported (H2a: $\beta = 0.206$, $p < 0.05$), whereas H2b is not supported (H2b: $\beta = -0.028$, $p > 0.1$). This indicates that managerial support cause easier AI adoption and that there is no positive relationship between technical capability and AI adoption.

H3a, H3b, H3c, H3d, and H3e are all supported (H3a: $\beta = 0.803$, $p < 0.01$; H3b: $\beta = 0.758$, $p < 0.01$; H3c: $\beta = -0.304$, $p < 0.01$; H3d: $\beta = 0.803$, $p < 0.01$; H3e: $\beta = 0.827$, $p < 0.01$). This indicates that managerial capability is significantly related to innovation attributes of AI. Stronger managerial capability creates a better IT environment for AI adoption and reduces the difficulty of applying AI technologies. Managerial capability is positively related to compatibility and relative advantage and is negatively related to complexity. Managerial capability also significantly influences the other organizational capabilities, including managerial support and technical capability. Higher managerial capability may get more managerial support and increase technical capability accordingly.

H4b, and H4c are not supported, whereas H4a and H4d is supported (H4a: $\beta = 0.107$, $p < 0.1$; H4b: $\beta = 0.04$, $p > 0.1$; H4c: $\beta = 0.036$, $p > 0.1$; H4d: $\beta = 0.113$, $p < 0.05$). These results suggest that

market uncertainty and competitive pressure do not play a role in the process of AI adoption, but government involvement and vendor partnership are critical factors for AI adoption. This means that good vendors and supplier partnerships can help firms adopt AI and government involvement can influence AI adoption. However, there is no positive relationship between AI adoption and market uncertainty and competitive pressure, respectively.

In terms of the control variables, none of the firm size, annual sales, and enterprise affiliation have a significant effect on AI adoption. One possible reason is that all the state-owned telecom operators in this study have a centralized management structure. Strategic plans, such as AI adoption, are developed by their headquarters. Therefore, firm size and affiliation levels do not affect the adoption of AI. Similarly, Huebner (2017) finds that organizational size is not significantly related to data mining success. However, larger firms are found to invest more readily in IT innovation (Low, Chen, & Wu, 2011; Oliveira et al., 2014). Research on the effects of firm size on IT adoption generates different results. Studies investigating different organizations in different industries may have different findings (Fu, Kok, Dankbaar, Ligthart, & Riel, 2018).

4.4.2.2 The additional study

In the main study, two factors of the external environment have no significant relationship with AI adoption. In order to explore the role of these external environment factors, an additional study is conducted using the same sample. The updated research model is shown in Figure 11. Three external environment factors are changed their positions. And the relationship between them and managerial capability is tested.

It is well known that government regulations will largely affect the business development of operators. The orientation of the regulatory policy determines the overall industrial structure to a

certain extent. The main study indicates that government involvement is a critical determinant during the AI adoption process. According to the Government Work Report at the Second Session of the 13th National People's Congress, the Chinese government requested that the average tariff for SMEs be reduced by 15% and the average tariff for mobile network data would be reduced by more than 20% during the year. In addition, the "Carrying number to network" will be implemented nationwide before the end of the year. This move will bring more severe pressure on China's three major operators. They need to adjust their development strategies, make practical package plans to maintain and attract subscribers to increase revenue, and strengthen operational management, improve operational management efficiency to reduce expenditures, and then minimize the negative impact of policies on company operations. Thus, the following hypothesis is proposed.

H5a. Government involvement is positively related to managerial capability.

Market uncertainty is another external environment factor. The rapid development of the Internet has completely changed the living environment of telecom operators. Internet-based services such as voice, SMS, and video calling have brought enormous challenges to the traditional services of telecom operators. Although the profits of global telecom operators in recent years have been affected by the impact of Internet companies, the arrival of big data and mobile Internet era has brought unlimited opportunities to telecom operators. Uncertainty in the 5G business model and economic benefit increase the market uncertainty. For operators, their development strategy and investment construction plan must consider market uncertainty. Therefore,

H5b. Market uncertainty has a significant relationship with managerial capability.

Competitive pressure is everywhere in the telecom market. With the rapid development of the Internet economy, the business of Internet companies such as Skype, Facetime, and WeChat has gradually eroded the core profit points of traditional telecom operators. People are getting used to texting, making phone calls, and even making video calls through various mobile apps. The dependence of users on traditional voice and short message services provided by telecom operators is declining, and the profits of operators are beginning to decline. Telecom operators' competitors are not just other operators. Their most powerful competitors have turned into the fastest-growing, flexible, and creative Internet giants in recent years, such as Google, Skype, Tencent, and other Internet companies. Operators must realize the changes in market structure and take corresponding measures. In addition, a firm's competitive advantage is not long-lasting, a managerial strategy needs to keep up with the competitive market situation. This leads to the following hypothesis.

H5c. Competitive pressure has a significant relationship with managerial capability.

Vendor partnership is not a complete external environment factor because the company will be involved. Therefore, in this additional study, unlike other external environment factors, vendor partnership doesn’t change its position, but the relationship between vendor partnership and managerial capability is tested. At present, new technologies in the telecom industry are emerging one after another, while telecom operators are facing the disappearance of the demographic dividend and the dilemma of “incremental increase without incomes”. On the other hand, the Internet has brought huge business opportunities. In order to seize the opportunities of the digital economy, it is necessary for operators to integrate more IT technology ideas and build comprehensive IT integration capabilities based on traditional business. Operators should actively cooperate with vendors to jointly innovate and promote industrial development. It can be said that

the firm managerial strategy will influence the way and extent of cooperation with vendors. This leads to the following hypothesis.

H3f. Managerial capability is positively related to vendor partnership.

The results of the suitability of the updated structural model and the research hypotheses are shown in Figure 11 and Table 10. The value of $\chi 2$ for the updated structural model is 1408.48. The ratio of $\chi 2$ and the DF is 2.056. CFI is 0.917. RMSEA is 0.061. All the values meet the generally accepted threshold for satisfactory, indicating the good fit of the updated structural model.

All the standardized path coefficients are significant at the level of $p<0.1$ or higher except the path H2b "Technical capability→ AI adoption." The value of R^2 is .672 in the updated research model, which indicates that the model is significant explained AI adoption. H1a, H1b, H1c which are related to the innovation attributes of AI are all supported (H1a: $\beta= 0.417$, $p < 0.01$; H1b: $\beta = 0.144$, $p < 0.05$; H1c: $\beta= -0.241$, $p < 0.01$). H2a is supported (H2a: $\beta= 0.201$, $p < 0.01$), and H2b is not supported again (H2b: $\beta= -0.031$, $p > 0.1$). The results are the same as the main study.

H3a, H3b, H3c, H3d, and H3e are all supported again (H3a: $\beta= 0.814$, $p < 0.01$; H3b: $\beta = 0.753$,$p < 0.01$; H3c: $\beta= -0.312$, $p < 0.01$; H3d: $\beta= 0.805$, $p < 0.01$; H3e: $\beta= 0.821$, $p < 0.01$). The results are also same to the main study. H3f is supported (H3f: $\beta= 0.678$, $p < 0.01$). This indicates that managerial capability positively influences the vendor partnership. Higher managerial capability can build better partnership with vendors.

H4d is supported again (H4d: $\beta= 0.103$, $p < 0.1$). That means vendor partnership still significant influence AI adoption and managerial capability has a strong significant positive relationship with vendor partnership.

H5a, H5b, and H5c are supported (H5a: β= 0.174, p < 0.05; H5b: β = 0.153, p < 0.1; H5c: β= 0.418, p < 0.01). These results suggest that although some of the external environment factors do not play a role in the process of AI adoption, government involvement, market uncertainty, and competitive pressure can significantly influence the managerial capability.

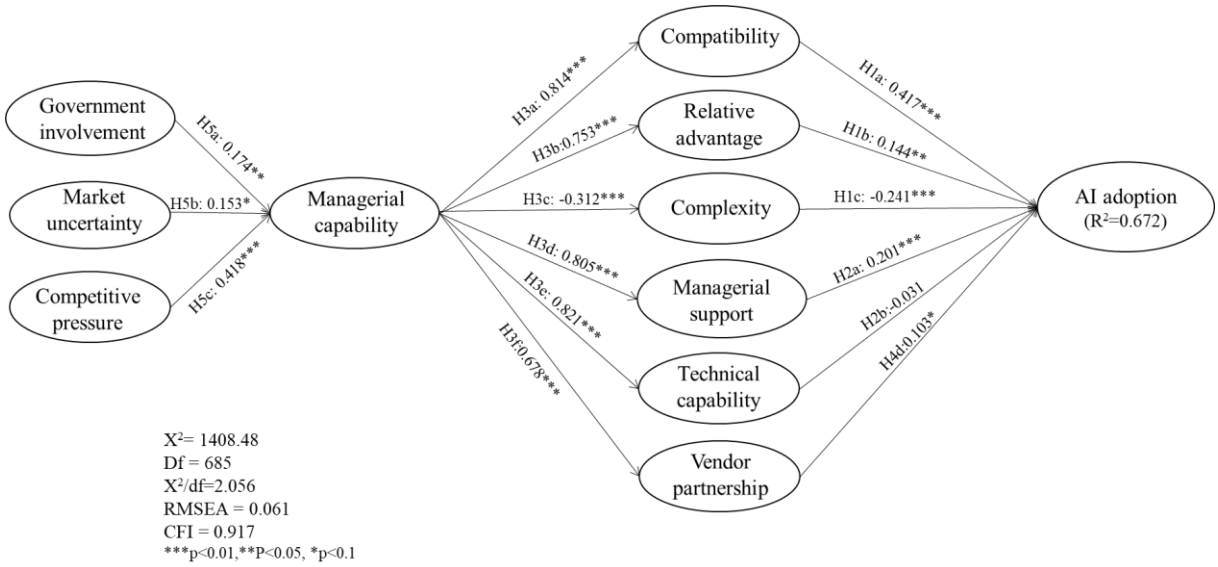

Figure 11. Updated Structural Model for the Additional Study

Table 10. Summary of Hypotheses Test Result for the Updated Structural Model of the Additional Study

	Paths	Standard path coefficient	p-value	Results
H1a	Compatibility → AI adoption	0.417	***	Support
H1b	Relative advantage → AI adoption	0.144	0.020**	Support
H1c	Complexity → AI adoption	-0.241	***	Support
H2a	Managerial support → AI adoption	0.201	0.008**	Support
H2b	Technical capability→ AI adoption	-0.031	0.675	Not support
H3a	Managerial capability→ Compatibility	0.814	***	Support
H3b	Managerial capability→ Relative advantage	0.753	***	Support
H3c	Managerial capability→ Complexity	-0.312	***	Support
H3d	Managerial capability→ Managerial support	0.805	***	Support
H3e	Managerial capability→ Technical capability	0.821	***	Support
H3f	Managerial capability → Vendor partnership	0.678	***	Support
H4d	Vendor partnership → AI adoption	0.103	0.079*	Support
H5a	Government involvement→ Managerial capability	0.174	0.013**	Support
H5b	Market uncertainty→ Managerial capability	0.153	0.063*	Support
H5c	Competitive pressure→ Managerial capability	0.418	***	Support

*P<0.1, **P<0.05, *** p<0.01 (Mithas et al., 2011; Pavlou et al., 2007; Wang et al., 2013)

5. STUDY 2---SUSTAINABLE GROWTH RESEARCH

5.1 Research purpose

With the continuous implementation of the national speed-up and fee-reduction policy, the vigorous promotion of broadband, and the extensive competition of "unlimited data" packages, the Chinese telecom operators have developed from the profit-making industry ten years ago to the current meager profit competition. The increasingly competitive market provides consumers with lower prices and better service quality putting pressure on operators' profitability. In addition, as mentioned above, with the rise of Internet companies, the three major operators in China are facing a more serious dilemma, and it is an urgent problem to be solved. Although the value of annual revenue keeps increased from 2007 to 2018, the annual revenue growth rate in these operators indicate a declining trend, as shown in Figure 12. China's unique regulatory environment, as well as China's unique consumer philosophy and cultural traditions, such as the deep preference for free services, make these three telecom operators face even higher pressure than international counterparts. Therefore, for these operators, how do they maintain sustainable growth?

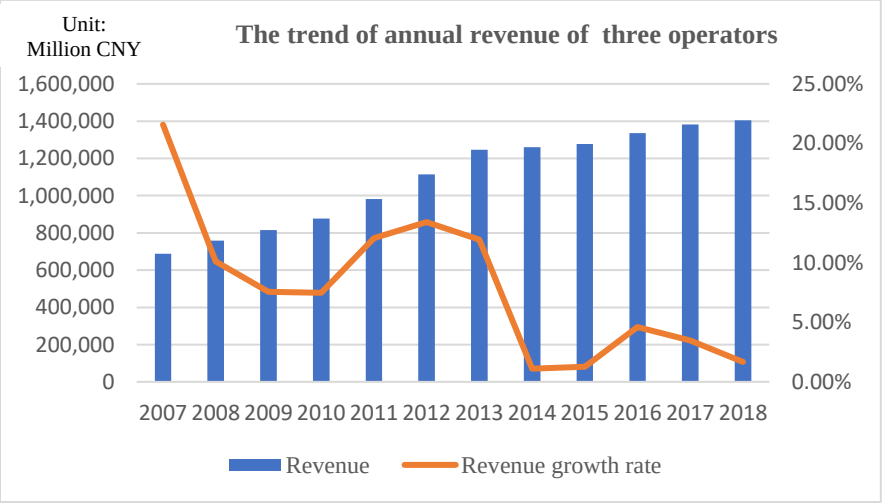

Figure 12. The Trend of Annual Revenue of Three Operators (data source: Bloomberg)

For operators, the commercial use of 5G and the application of AI will promote the deep penetration of digital technology in the whole society, and bring opportunities for operators to establish new profit models, but in addition to waiting for the huge 5G era dividends, what factors inside and outside the operators will affect their sustainable growth? Based on the Resource-Based View, using longitudinal time-series panel data, this study explores the key factors affecting firm sustainability from the perspective of firm-level customer value and operational efficiency, as well as industry-level investment.

5.2 Hypotheses and framework

The company's resource-based view (RBV) stems from the notion that company performance is determined by the resources it owns. The use and configuration of these resources enable the company to fulfill and provide a unique competitive advantage (Barney, 1991). These resources include tangible and intangible assets. For telecom operators, subscribers are the most important resource, which is the base of revenue. The profitability of these operators is related to their subscribers' base, which depends on the number of active customers, the duration of customer calls and services (Ishaya & Folarin, 2012). Therefore, operators make every effort to attract new customers and keep existing customers to maintain a competitive advantage. However, it's not enough to have only the number of customers, and the quality of the customer is also essential. Customer value is an important part of maintaining a company's sustainable competitive advantage. High-value customers contribute more to the company.

Operational efficiency is another intangible resource. For these operators, operational efficiency should be a key factor in achieving higher revenues and increasing market position. From a financial perspective, operational efficiency means using less operating expense to gain more

revenue. The telecom operators need to maintain sustainability, financial stability, and profitability, especially when we know that the mobile phone penetration rate in China exceeded 112% as per MIIT statistics, which means the possibility for revenue growth is declining year after year. Accordingly, all telecom companies need to control cost and expense to achieve efficiency.

Government support and industry investment is another critical resource for these operators. As state-owned enterprises, the government plays a crucial role during the development process of telecom operators. In 2018, the Chinese government asked the three operators to cancel the charge of mobile data roaming, increase broadband speeds, and reduce tariffs, which undoubtedly put more pressure on their performance growth. Telecom operators are endeavoring to attract investment from the government to fund the rapid growth of telecommunication infrastructure and related value-added services. Unlike operators in the US operating based on capital operations, although the three operators are commercialized, they also have to take social responsibility to ensure that each user has access to communications and Internet resources, which can decrease their profitability. Profitability reflects the company's ability to generate profits in order to sustain their business. Therefore, the support of regulatory and investment from the government is important to keep sustainable growth for these operators.

In consequence, three hypotheses are proposed:

Hypothesis6: Customer value positively impacts firm sustainable growth

Hypothesis7: Firm operational expense negatively impacts firm sustainable growth

Hypothesis8: Industry level investment positively impacts firm sustainable growth

The conceptual framework of this study, as in Figure 13, shows that the customer value and operational expense both influence firm sustainable growth, and the industrial investment has a positive effect on firm sustainable growth, too.

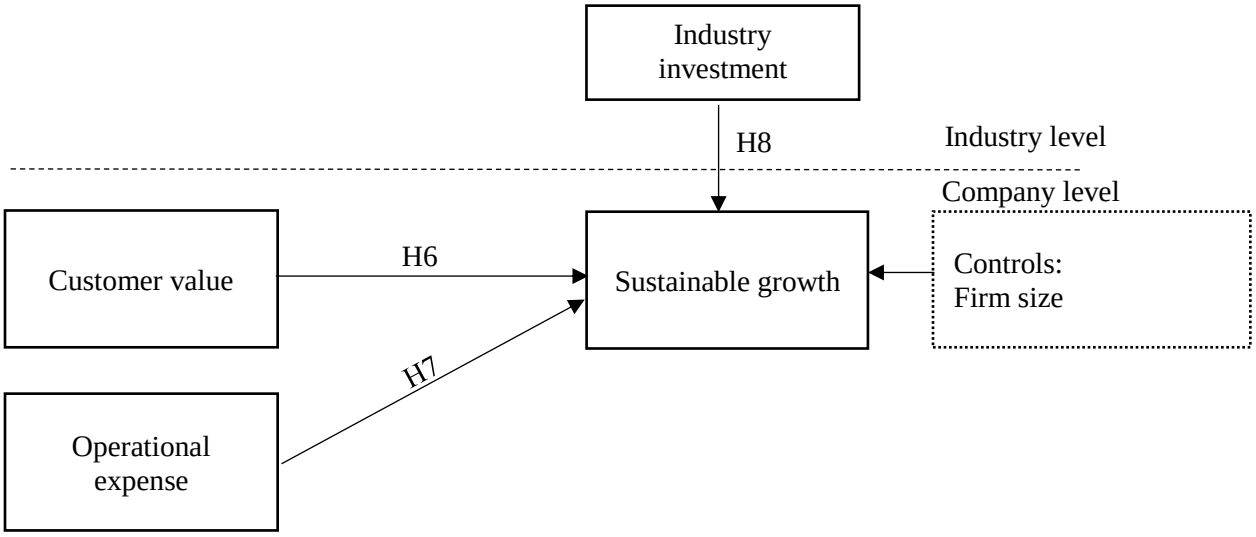

Figure 13. Research Framework of Study 2

5.3 Data and samples

The study explores the internal and external factors that impact the telecom company sustainable growth using company level and industry level data over time. The research sample draws from the major telecom operators in China, including China Mobile, China Telecom, and China Unicom.

The annual firm-level data was collected from Bloomberg with the period ranges from 2006 to 2018. The annual industry-level data is collected from the Annual Statistical Bulletin of Communications and Operations of the MIIT from 2005 to 2016. Because the benefit of intellectual capital has a lagged effect, the data between industry investment and customer value, operating expense, and sustainable growth has a one-year lag.

5.4 Variables and measures

Independent variables (firm level)

Following previous research, this study adopts the average revenue per user (ARPU) (Livne, Simpson, & Talmor, 2008; McCloughan & Lyons, 2006) and operating expense as a percentage of revenue (Proenza, 2001) to proxy customer value and operational expense.

ARPU is a benchmark for the profitability of a company (Gruber,1999). For telecom operators, ARPU is one of the most important business parameters which refers to an indicator of how much revenue per user per month/per year brings to the telecom operators. It is a key metric used by analysts to track telecom companies and markets (McCloughan & Lyons, 2006), which is usually applied to measure the profitability of business and value of intellectual capital. ARPU represents the average revenue generated by each customer of the company. The fierce competition in telecom services has enabled the telecom companies to acquire new customers or retain existing customers by lowering the tariffs on telecommunications services, which will reduce the ARPU.

Operational expense is measured by operating expense as a percentage of revenue (OEPR). OEPR= Operating expense/ Revenue. The total operating expense of telecom operators mainly includes maintenance fees, depreciation, selling expenses, and personnel. The higher the OEPR, the lower the operational efficiency. The telecom industry benefits from the favorable development of equipment and operating costs, reducing the average cost per user. But the intense market competition forces operators to increase their operating expenses. For example, to attract subscribers to the aggressive market, operators need to cost higher expenses for sales promotion.

Independent variable (industry level)

Industry investment is measured by industry fixed asset investment (IFAI). The telecom industry is a technology-oriented industry. The development and application of new communication technologies have greatly promoted the development of the industry. The upgrading of communication technology accompanies the scale of telecom fixed investment, showing obvious periodicity. In January 2009, China's MIIT issued 3G licenses, which led to a peak in the scale of telecom investment in 2009. The 2013-2014, 4G licenses were issued one after another, and telecom fixed asset investment once again created a new growth peak. The maturity and large-scale construction of 4G technology drive corresponding large-scale infrastructure investment. And the upcoming commercial 5G network is bound to trigger a larger investment in fixed assets. Industry-level fixed asset investment brings momentum to operators.

Dependent variable

Regarding the measurement of firm financial performances, sustainable growth rate (SGR) is used to measure sustainable growth based on accounting measures. SGR refers to the maximum growth rate that a company can sustain without having to fund growth through additional equity or debt. The SGR involves maximizing sales and revenue growth without increasing financial leverage (Hartono & Utami, 2016; Murphy, 2019).

$$\text{SGR}=\text{Return on equity} \times (1-\text{Dividend payout ratio})$$

Return on equity (ROE) measures the company's profitability by comparing the net income or profit of the company's issued shares or shareholders' equity. The dividend payout ratio is the percentage of earnings per share paid to shareholders (Murphy, 2019).

Control variable

As a control variable, firm size is measured by the number of employees (NOE). As one of the typic characteristics of a company, firm size is often used as a control variable (Garrison et al., 2015; Liang, Saraf, Hu, & Xue, 2007). For telecom companies, the revenue is also applied to measure the firm size. But for this study, because there is high collinearity between revenue and SGR, which is not suitable for this study.

Table 11 provides information regarding the mean values, standard deviations, and bivariate correlations between the variables.

Table 11. Correlation Matrix for Sustainable Growth Rate and Its Predictors in Three Companies

Variable	Mean	S.D.	SGR	NOE	ARPU	OEPR
Sustainable growth rate (SGR)	5.915	4.509				
Number of employees (NOE)[a]	12.362	.337	-.621***			
Average revenue per user (ARPU) [a]	3.810	.547	.780***	-.221		
Operating expense as a percentage of revenue (OEPR) [a]	4.453	.130	-.940***	.625***	-.747***	
Industry fixed asset investment (IFAI) [a]	5.846	.210	-.599***	.704***	-.451**	.692***

Notes: [a] Log-transformed to assure normality.
* * Significant at the 0.01 level; *** Significant at the 0.001 level;

5.5 Analytical method and empirical model

Multiple regression model is used to test the hypotheses. The test is based on changes in the level of explained variation before and after the variable of a different level is added to the control variable. The following is the empirical model:

$$SGR=\beta_1+\beta_2*NOE+\beta_3*ARPU+\beta_4*OEPR+\beta_5*IFAI+\varepsilon$$

Where, SGR represents the firm sustainable growth rate. NOE represents the number of employees. ARPU represents the average revenue of per user. OEPR represents the operating expense as a percentage of revenue. IFAI represents the industry fixed asset investment. ε represents the error term.

5.6 Empirical results

Table 12. Multilevel Regression of Firm Profitability and Operational Efficiency Impact on Sustainable Growth

Variable	Model1		Model2		Model3	
	β	Standard error	β	Standard error	β	Standard error
Constant		24.952		16.262		15.156
Controls:						
Number of employees (NOE)	-.621****	2.018	-.162	1.172	-.260**	1.243
Firm-level predictors:						
Average revenue per user (ARPU)			.266*	.849	.291**	.796
Operating expense as a percentage of revenue (OEPR)			-.639***	4.457	-.695***	4.246
Industrial-level predictors:						
Industry assets investment					.195*	1.916
Degrees of freedom(df)	27		25		24	
F value	16.962***		83.635***		73.437***	
R^2	.386		.909		.924	
ΔR^2			.524***		.015*	

Notes: * Significant at the 0.05 level; ** Significant at the 0.01 level; *** Significant at the 0.001 level.

Table 12 presents the two-level regression results. Model 1 includes only the control variable. The number of employees is significantly negatively related to firm sustainable growth. A large number of employees could decrease productivity and increase operational expenses, which hinders the firm sustainable growth. Model 2 contains two firm-level direct effects. The inclusion of the firm-level independent variables increases the explanatory power for SGR significantly (Δ R2 =.524, p<0.001). In accordance with prior literature (McCloughan & Lyons, 2006), the APRU of subscribers really can provide additional information in explaining the variation of firm sustainable growth. The whole model attains a significant level (F=83.635, p<0.001) and explains the variation of 90.9 percent in firm sustainable growth. These two indicators are consistent with hypotheses 6 and 7. Customer value (ARPU) is positively associated with firm sustainable growth. The operational expense (OEPR) negatively influences firm sustainable growth, which means high OEPR refers to low operational efficiency, which can block the development of the firm.

In model 3, the control variable, two firm-level effects, and one industry level effect are regressed. All three effects are statistically significant. Hypothesis 8 is also supported. Industry assets investment significant positively impacts firm sustainable growth.

In addition, significant changes in the adjusted R2 provide support for the hypotheses. When passing from model 1 to models 2 and 3, the increases of R2 are significant. The results provide relatively strong support for its predictions related to firm sustainable growth. Both internal and external factors were found to influence firm sustainable growth directly.

5.7 Model evaluation and selection

Before building a model (for example, a linear regression model), we must accept that no model can produce all the truth or complete information about the phenomena being studied, but we can try to minimize the loss of information. Akaike's information criterion (AIC), developed by Akaike (1973), is an information criterion to estimate the goodness of statistical model fitting by which to rank competing models in terms of information loss in approximative unknowable truth. AIC is very useful in model selection. By comparing the AIC values of models, the model with the lowest AIC value is the best approximation model (Burnham, Anderson, & Huyvaert, 2011; Symonds & Moussalli, 2011). AIC is calculated as

$$AIC = -2\ln(L)+2k \text{ or } AIC = n\,[\ln(RSS/n)] + 2k$$

where L is likelihood, k is the number of estimated parameters included in the model, n is the sample size, RSS is the residual sum of squares (Symonds & Moussalli, 2011).

The AIC penalizes for the addition of parameters, and thus selects a model that fits well but has a minimum number of parameters (Mazerolle, 2006).

If the research sample size is small, we can use another modified version of AIC (AIC_c), like Symonds and Moussalli (2011) said, "for small sample sizes (roughly approximated as being when *n*/*k* is less than 40 and *k* is the number of fitted parameters in the most complex model), a modified version of AIC (AIC_c) is recommended: AICc=AIC+2k[(k+1)/(n−k−1)] "(Symonds & Moussalli, 2011, P.14)

In addition, two measures associated with the AIC can be used to compare models: the delta AIC and Akaike weights. The delta AIC (Δ_i) is a measure of each model relative to the best model and is calculated as Delta $AIC_i = \Delta_i = AIC_i$ – minAIC

where AIC*i* is the AIC value for model *i*, and min AIC is the AIC value of the "best" model (Burnham et al, 2011; Symonds & Moussalli, 2011).

Akaike weights (w_i) represent the ratio of the delta AIC (Δ_i) of a given model relative to the whole set of *R* candidate models: $w_i = \exp(-\Delta i/2)/(\sum_{r=1}^{R} \exp(-\Delta i\ /2))$(Symonds & Moussalli, 2011).

The three models of sustainable growth research are evaluated using AIC. The results are shown in Table 13 which indicates that model 3 with an Akaike weight of 0.84 is the best given the set of 3 candidate models.

Table 13. AICc of the Multiple Linear Regression Models

Model	k	AIC	AIC_c	delta AIC (Δi)	Akaike weights (*wi*)
1	2	76.1946	76.6561	54.7761	0.0000
2	4	24.6976	26.3643	3.2791	0.1625
3	5	21.4185	24.0272	0.0000	0.8375

6. DISCUSSION

The competition in the telecom industry is very intense. In order to maintain market share and competitive advantage, operators continue to improve their service quality, innovate products, and reduce service charges. Improper and fierce market competition leads to a dilemma of "incremental increase without incomes". In addition, the rise of internet companies gradually erodes the profit of traditional telecom operators. The telecom operators have moved from the profit-making industry ten years ago to the current meager profit competition. The increasingly competitive market provides consumers with lower prices and better service quality, putting pressure on operators' profitability. The unique regulatory environment and unique cultural traditions in China make telecom operators face even greater pressure than their international counterparts. The commercial use of 5G and the application of AI may bring opportunities for operators to establish new profit models. In addition, paying attention to the critical factors impacting firm sustainable growth can help operators get out of the predicament.

AI applications in the telecom industry are increasingly helping operators manage, optimize, and maintain their infrastructure, as well as their customer support operations. Telecom operators have focused their efforts on AI applications such as customer service chatbots, speech and voice services for customers, network monitoring and management, and generic telco AI platforms. According to our survey, 45% of respondents indicate that their company will first apply AI technologies for intelligent network monitoring and management, 33% of respondents believe they will build generic AI platforms, 15% of respondents think that they will adopt AI voice assistant, and 6.5% of respondents consider to apply AI chatbots. Currently, telecom operators in China have already deployed in the AI field, and the commercial application cases are shown in Table 14, but the application of AI in the field of communication is still in its infancy.

Table14. AI Application Cases of Telecom Companies in China.

Application cases	China Mobile	China Telecom	China Unicom	China Tower
Chatbots	Yiwa	Xiaozhi	Wobao	
Voice assistant	Lingxi	Xiaoyi	Xiaodu1C	
Intelligent Network	Network architecture "NovoNet"	Network architecture "CTNet2025"	Network architecture "CUBE-Net 2.0+"	National Internet of Things + Internet wireless monitoring system
Generic AI platform	Jiutian	Dengta	Cloud platform "TianGong"	

The goal of the main study and the additional study is to assess the determinants of AI adoption by using an integrative model that combines the innovation characteristics of AI with organizational and environmental factors. The results of the main study show that six factors directly influence AI adoption: compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership (see Table 9). The results also indicate that managerial capability highly influences other organizational capabilities and innovation attributes of AI and that managerial capability is indirectly related to AI adoption (see Table 9), and the external environment factors including government involvement, market uncertainty, and competitive pressure highly influence managerial capability (see Table 10). The goal of study 2 explores the critical factors influence firm sustainable growth using longitudinal time-series panel data. The results indicate that customer value, operational expenses, and industry investment significantly influence firm sustainable growth (see Table 12).

Regarding innovation attributes of AI, compatibility (H1a) is found to be positively related to AI adoption. This finding is consistent with previous studies reported in the literature review (e.g., Chong et al., 2009; Thong, 1999; Wang et al.,2010). Compatibility has a path with the greatest

magnitude in relationship with AI adoption, comparing with other innovation attributes of AI, managerial support, and vendor partnership. This indicates that firms concern about the compatibility of AI much more than other factors. Thus, the compatibility of AI is noteworthy. Currently, although the services of telecom operators are more complicated than before, the network is still their most basic and important asset. This study shows that 45% of the respondents believe that their company will first adopt an intelligent network. In other words, the intelligent network is very likely to be adopted by the telecom industry. Therefore, the compatibility of AI with their current network becomes the key issue for telecom operators. Oliveira et al. (2014) find that compatibility is a facilitator for cloud-computing adoption in the services sector but not in the manufacturing sector. They point out that the work style preferences and Internet-based business operations in the service sector are a difference from those in the manufacturing sector. Because telecom is in the service sector, the finding in this study about compatibility is consistent with the findings in Oliveira et al. (2014).

Relative advantage (H1b) is found to be positively related to AI adoption as well. This finding confirms that organizations recognize the relative advantage of AI. The advantages of AI technologies and applications identified by this study include improving customer service and experience, increasing employee productivity, and better utilizing IT resources. Complexity (H1c) is found as an inhibitor to AI adoption. Complexity is associated with AI just as how it is associated with other disruptive technologies. This study proves that complexity is an important determinant in AI adoption. AI adoption is not a simple plug and play project for telecom operators. Instead, a huge amount of network construction and operation is required. However, telecom operators lack the expertise of AI. Therefore, complexity is associated with the perception of changes, which cause discomfort and frustration (Oliveira et al., 2014).

In terms of organizational capability, the results of these studies provide empirical evidence to support that managerial support (H2a) is a driver for AI adoption. Managers can promote AI adoption by engaging in the process and coordinating organizational resources. Top managers also can determine the mission, vision, policy, and direction of employees in order to drive IS projects to successful completion (Intakhan, 2014). It is important for AI adoption that the top managers in a firm can leverage AI applications as a strategic core competency. This finding is consistent with the results in earlier studies on the adoption and use of innovative technologies (Oliveira et al., 2014; Wang et al., 2010; Yang, Sun, Zhang, & Wang, 2015).

The technical capabilities are not positively related to AI adoption (H2b). AI adoption in firms with established technology infrastructure and technical competence might not be easier than it is in firms with undeveloped technology infrastructure and low technical competence. Some studies find that technical capabilities do not play a role in firms' IT adoption. For example, Low, Chen, and Wu (2011) find that technological readiness is not a concern for firms in the technology sector. Wu, Cegielski, Hazen, and Hall (2013) find that firms with greater information-processing capacity are less likely to adopt cloud computing. Telecom operators are high-tech firms. They need to keep their technology infrastructure up to date and let their employees have cutting-edge technical capabilities to gain competitiveness. It does not matter for them to adopt AI technologies or not. In contrast, other studies find that technical capabilities do facilitate IT adoption (e.g., Garrison et al., 2015; Oliveira et al., 2014). The degree of disrupting services and challenges for management caused by implementing disruptive technologies may vary across IT and non-IT firms. Therefore, the roles of technical capabilities are mixed and require more investigation to reach more definite conclusions.

Managerial capability is highly related to innovation attributes of AI, other organizational capabilities, and vendor partnership (H3a, H3b, H3c, H3d, H3e, H3f). Thus, the managerial capability is indirectly related to AI adoption. Higher managerial capability can increase managerial support and technical capability, increase the compatibility of AI implementation, enhance the perception of the advantage of AI application, and weaken the perception of the relative risk of AI applications. Although higher managerial capability is related to higher AI adoption, managerial capability does not impact AI adoption directly. Firms' managerial capability influences AI adoption through managerial support and all the innovation attributes of AI. In addition, the managerial capability positively influences the vendor partnership. Composite digital service providers become the inevitable path for operators' transformation. The adjustment of business strategy and the change of management mode will inevitably affect the cooperation mode and content with vendors.

Previous studies find that variations in the external environment affect IT adoption decisions (Gibbs & Kraemer, 2004; Low et al., 2011). The external environment factor, government involvement, is a critical factor that affects AI adoption (H4a). Firms studied in this study are all state-owned companies. In China, the government controls state-owned enterprises such as telecom operators from the two aspects of policy guidance and maintaining and increasing the value of state-owned assets. The government controls the operator's business scope by issuing licenses, such as 5G licenses; and manages the operator's business strategy by appointing the top managers. With the successive release of the State Council's A Next-Generation Artificial Intelligence Development Plan (Creemers, 2017) and the Ministry of Industry and Information Technology's Three-Year Action Plan for Promoting Development of a New Generation Artificial Intelligence Industry (2018-2020)(Beckett & Ge, 2017; Dutton, 2018), AI has risen to the national

strategic level in China. The government provides a favorable environment for encouraging the development and deployment of AI applications. In addition, government policies highly influence telecom operators in China. The "broadband China" strategy implantation plan expanded the coverage of fiber broadband networks, improved 3G and 4G communication, and increased the number of broadband subscribers. The policy of canceling charges of mobile data roaming reduced the profit margin of operators. As state-owned companies, Chinese telecom operators benefit a lot from the resources and policies provided by the government; at the same time, some policies give them negative effects. Thus, the government regulatory environment is important for telecom operators, government involvement can influence their AI adoption decision.

Market uncertainty and competitive pressure are not positively related to AI adoption (H4b, H4c). Some IT adoption studies report that variations in the external market environment affect IT adoption decisions (Hannan & McDowell, 1984; He, 2015; Lovely & Popp, 2017). They find that when a firm is facing fierce competition, it has strong incentives to find innovations that can help it maintain and enhance its competitive advantages. However, this study does not find a positive relationship between competitive pressure and AI adoption. For telecom operators, it is precarious to change their IT infrastructures. Operators are the core driver of the AI industry. On the one hand, the 5G networks are inseparable from AI technology. On the other hand, operators are also the platform and carrier of big data that support the entire intelligent industry chain. The operator's own business development needs and the demand of the entire industry chain prompt them to adopt AI technologies and applications no matter how uncertain and competitive the market is. Similarly, Ifinedo (2011) finds that determines which pressure from customers, business partners, and government support do not play significant roles in technology adoption.

Additionally, the study finds that vendor partnership is positively related to AI adoption(H4d). Partner collaboration is a significant facilitator for AI adoption. Vendors play a unique and important role in the field of AI. Usually, firms do not have all the expertise and experts to support innovations, such as AI applications. Independent research and development AI require huge funds and excellent talents as support. Vendors also need all the necessary data from their customers. Thus, it's wise for firms to work with AI vendors and partners to implement AI applications. The right AI technology vendors can provide an efficient way of cooperation and ensure that cooperation strengthens rather than weakens the competitive advantage of the company. Consequently, firms should build networks with partners and share resources to meet market demands better and to gain more competitive advantages. The finding regarding vendor partnership in this study is consistent with the finding in Oliveira and Martins (2010), which notes that trading partner collaboration is a significant facilitator for the tourism industry and telecom industry.

The additional study explores the role of external environmental factors. We can see that although market uncertainty and competitive pressure are not significantly related to AI adoption, the external environment factors strongly influence the managerial capability (H5a, H5b, H5c). This validates the TOE framework from a certain perspective, which means technological, organizational, and environmental factors do influence the adoption process.

Overall, the results support the proposed model regarding success factors for AI adoption. The factors include innovation attributes of AI, organizational capability, and external environment. The findings confirm the role that these factors play in IT adoption. Particularly, the managerial capability is an indirect factor that is positively related to AI adoption. In addition, the TOE framework is proved to be effective for examining the success factors of AI adoption.

For the study 2 of sustainable growth research, all the three hypotheses are supported, which indicates that customer value, operational efficiency, and industrial investment are critical factors of firm sustainable growth (H6, H7, H8). In order to maintain firm sustainable growth, on the one hand, operators need to mine customers' new requirements and expand ARPU service sources through innovative business applications. On the other hand, they can promote the growth of customer numbers with low tariffs, lower the threshold for business use, and increase ARPU through the increase in service usage. But operators should reduce tariffs according to market demand and cannot aggressively attracting customers at low prices. Otherwise, the sharp decline in customer value will affect the company's profitability. The company is unable to conduct future network R&D and construction investment, resulting in a decline in the quality of telecommunications services, thus losing the momentum of sustainable development. Operators also need to reduce various management costs, decrease expenditures reasonably to improve operational efficiency. It is not advisable to reduce network investment and reduce employee wages to cope with the increasingly fierce price war and improve the company's profit margin in the short term. The finding also indicates that government support and industry level investment significant influence on firm sustainable growth. Operators should strengthen cooperation with the government to maximize financial support and achieve sustainable development.

6.1 Implication for research

This paper makes important contributions to research on AI adoption. First, some scholars call for a holistic approach that combines more than one theoretical perspective to study IT adoption which involves innovative new technologies in recent years (Fichman, 2004; Lyytinen & Damsgaard, 2011; Xu, Thong, & Tam, 2017). But few studies on AI adoption are available now. As such, this study bridges the gap. Particularly, this study proposes a conceptual framework by integrating the

TOE framework with DOI theory to validate the determinants of AI adoption. Innovation characteristics of AI, organizations, and environmental contexts of organizations are embedded in the framework. This study is different from previous researches on AI adoption because it empirically validates the indirect effects of the antecedents of AI adoption for the first time. This study finds that (a) innovation attributes of AI are factors that affect AI adoption; (b) managerial capability affects other factors but impacts AI adoption indirectly; (c) external environmental factors including government involvement and vendor partnership affect AI adoption except. The findings validate the results in previous researches regarding factors that impact IT adoption. In addition, the instrument applied in this study is verified by reliability and validity tests. Moreover, both the main research model and the additional research model have a good global fit. Therefore, the instrument and the research models could be applied in other studies on innovations.

Second, the research highlights that not only the characteristics of AI technologies but also technology capabilities affect AI adoption. Although these studies find that technology capability is not positively related to AI adoption based on the data collected in the telecom industry, studies collecting data from other industries might generate different findings. Because technology capability has not been fully investigated by existing technology adoption literature, more researches are required to explore the role of technology capability.

Third, the research offers a new and unique perspective for IT adoption literature. Most IT adoption studies to date are conducted in developed countries, especially in the U.S. (Chau & Tam, 1997; Lai, 2017). This research explores AI adoption based on the data collected in China. The findings provide a new lens to see IT adoption. Furthermore, existing technology adoption studies find that innovation and diffusion occur unevenly in different environments across countries. In other words, the extent of innovation and diffusion depends on economic, social, and political factors (Caselli

& Coleman, 2001; Tornatzky & Fleisher, 1990). Therefore, it is necessary to investigate whether existing adoption models can be generalized and whether findings in existing technology adoption literature are applicable in different cultural and economic contexts (Venkatesh, Bala, & Sambamurthy, 2016). To this end, this research validates factors affecting technology adoption in a different context. In sum, the models provide a sound basis for future endeavors in this direction.

Forth, the research contributes to the sustainable growth research literature by exploring factors that influence firm sustainable growth using panel data from major telecom operators in China. It's also a unique perspective because very few types of research focus on sustainable growth research in the telecom industry in China. By using multilevel modeling techniques, the results suggest that at the firm level, besides technology innovation, increasing the ARPU of subscribers and decreasing the operating expense can improve firm sustainable growth. The findings also suggest that the industry level investment is critical to the sustainability of telecom operators.

6.2 Implication for practice

The findings in the main study and the additional study provide practical implications for firms that would like to deploy AI technologies and applications effectively. Understanding the determinants of AI well is paramount for firms that consider adopting AI. These studies provide firms insights to be well prepared for implementing AI technologies and applications. First, firms should acquire abilities, particularly managerial ability, to adopt new technologies effectively. The efficient internal management mechanism is key for implementing new technologies smoothly. The findings in this study indicate that firms must ensure the efficiency of internal cooperation and communication as well as the integrity and effectiveness of education and training programs to integrate AI-based solutions in their business operations with minimal interruption. In addition,

the findings provide decision-makers a sound basis to estimate the direct and indirect effects caused by the innovation characteristics of AI.

Second, the findings show that vendors and partners play a significant role in helping firms adopt AI technologies. Algorithms and models are the core of AI, but many firms knew little about algorithms and models. Thus, AI training offered by vendors can alleviate technological barriers in AI adoption (Hung, Huang, Yen, Chang, & Lu, 2016). Garrison et al. (2015) point out that inter-organizational relationship is a key resource that explains differences in advantage among firms. AI vendors have different skill levels. Firms may increase competence by leveraging vendors' capabilities and incorporating best practices into their AI adoption. Therefore, firms need to cooperate with suitable AI vendors fully and to utilize their expertise to achieve a win-win situation.

Third, the findings provide valuable insights for managers to make informed AI decisions. AI is not an IT innovation only, but strategic creativity. It represents a huge shift in the business model for firms to achieve business efficiency and to gain competitive advantages. The identification of the determinants of AI adoption may support managers when they make decisions about AI adoption and help them allocate resources or change procedures for implementing AI adopting successfully.

Forth, according to the unique characteristics of telecom operators, this research also provides several suggestions of AI adoption to these operators: 1) Enhance the company's comprehensive managerial capabilities, that means operators need rationally allocate enterprise IT resources, establish effective internal communication and collaboration mechanisms, develop feasible education and training programs, reduce the difficulty of AI applications, and create conditions for AI applications. 2) With the deployment of 5G networks, AI technologies should be fully introduced to make network operation and maintenance more automatic and intelligent, to improve

operational efficiency and save operation and maintenance costs. At the same time, because the huge mobile network generates rich data, operators could actively use AI and Big Data technologies and platforms to mine data, improve data quality, enhance data processing efficiency, and ensure data security. It's worth to extract the data that was not collected in the past and discover the value from it using AI technology. 3) Vendors partnership plays a significant role in AI applications. Operators can collaborate with AI vendors in a variety of ways, such as outsourcing the entire process, purchasing specific services, allowing suppliers to assist in developing internal solutions or training internal staff. Operators should actively cooperate with AI vendors and industry users (such as power, public security, transportation and other industries), research and explore innovative services and applications based on 5G+AI, provide different application scenarios for different business needs, maximize resource utilization, and use AI to make all the industries on the chain profitable. 4) It is necessary to establish a reasonable and innovative AI talent mechanism. Operators should focus on cultivating compound talents who understand both telecommunications networks, business and operations, and AI. At the same time, through the development of appropriate systems and incentives to guide employees to develop and upgrade their own potential and technology to integrate human resources and improve the overall efficiency of the company.

Finally, study 2 also provides empirical insights for firm sustainable growth in the telecom industry. It reveals that firm sustainable growth is influenced at both the firm and industry level. Customer value is significant. Facing fierce competition and nearly saturated market, operators should not blindly attract low-end users at low prices. In order to maintain firm sustainability, it is necessary to improve service content and quality, attract and stimulate customers to use services they provided, and strive to improve ARPU. Simple ways of directly reducing expenses, such as

reducing the compensation of employees and cutting channel agency expenditure to increase profits, are also not desirable, which is not conducive to the sustainable development of enterprises. The role of government regulation cannot be underestimated. The rational allocation of resources and striving for government policies and financial support can also promote firm sustainable development.

7. LIMITATIONS AND FUTURE RESEARCH

This research has several limitations that should be taken into consideration. First, the sample of the research only includes the telecom companies in China. Therefore, it reflects the situation in one industry and one nation only. Furthermore, this research does not explicitly incorporate cultural and industry-specific factors into the research model. These factors might have moderating effects on the proposed relationships in the research model. Cross-industry and cross-country studies need to be conducted for enhancing the generalizability of the findings in this study. Comparisons between industries and countries could provide significant insights into the differences caused by industries and regions. It is therefore suggested to consider this point in future research.

Second, the accuracy of responses to the questions in the survey is depended on participants' truthfulness in their responses to the survey items, as well as their prior experiences and understanding with AI technologies and applications. Therefore, caution must be exercised in generalizing the results in this study to other contexts and types of AI technologies and applications. Future research needs to apply more objective approaches to validate the findings in this study.

Third, the TOE framework has no major constructs and specific variables in each context. The dimensions of technology, organization, and environment involve many factors, not just the ten factors examined by this study. Future researchers should investigate additional inter-firm relationship variables as well as other firm-specific capabilities to explore how they affect AI adoption.

Forth, sustainable growth research only explores several factors, including customer value, operating expense, and industry investment that could influence the firm sustainable growth. There

are so many resources inside and outside the company that may be related to firm sustainable growth, which need further research to discover and verify. In addition, customer value is measured by ARPU, which is a specific indicator in the telecom industry. Maybe ARPU is not suitable for some other industries. Thus, further research should pay attention to it.

8. CONCLUSION

AI has the disruptive potential to boost profits, transform industries, and fundamentally change society. At present, from the perspective of the number of enterprises, the major industries with more AI penetration include healthcare, finance, business, education, and public safety. AI is expected to become a big part of our daily life in the 2020s (Mitter, 2018). AI can create enormous benefits for companies, but it can also bring risks to make the company into a passive situation. For example, if a company is slightly careless, it may reveal valuable and sensitive information, thereby weakening its competitive advantage. If companies do not build internal managerial and technical capabilities, they run the risk of over-relying on suppliers. Although previous studies have proposed several critical factors that affect IT adoption, few studies empirically investigate the success factors that affect AI adoption. The success factors are the necessary enablers that lead to the successful implementation of AI. These factors play a key role in improving the probability of success in decision making. Firms need to evaluate these factors before adopting AI-based solutions systematically. Therefore, this research is aimed to explore the impacts of success factors on AI adoption from the perspectives of the external environment, organizational capabilities, and innovation attributes of AI. In addition, for the current development dilemma faced by the telecom operators, this study explores the factors affecting the sustainable growth of companies from both the firm and industry levels.

To this end, the main study develops a research model to investigate the determinants of AI adoption by integrating the TOE framework and the DOI theory. The study addresses three questions: (1) What factors are concerned by firms when they plan to adopt AI technologies? (2) How do the factors interrelate to influence the decision of AI adoption? (3) Do these factors affect AI adoption at the same level? The research model is empirically tested with data collected by

surveying telecom companies in China. Structural equation modeling is applied to analyze the data. A total of 10 factors are proposed to influence AI adoption critically. The results show that six factors, namely compatibility, relative advantage, complexity, managerial support, government involvement, and vendor partnership, directly affect AI adoption. Managerial capability impacts other organizational capabilities and innovation attributes of AI, but it is indirectly related to AI adoption. Previous studies found that the technical capability of the organization and external environmental factors, such as market uncertainty and competitive pressure, contribute to the success of IT adoption. However, the empirical results in this study indicate that these factors are not related to AI adoption. It should be noted that these factors might still exert influence in other situations, for example, in different industries or different countries. Based on the main study, the additional study tests the role of external environment factors and finds that although some of them are not critical determinants for AI adoption, all of them can influence the managerial capability, which indicates that the external environment factors are still significant in the whole adoption process. In addition, based on RBV, study 2 focuses on the impact of internal and external factors on the sustainable growth of the telecom sector. The research model is empirically verified with longitudinal time-series panel data collected from Bloomberg and the MIIT. Multiple regression model is used to test the hypotheses. The results show that customer value positively affects firm sustainable growth, operating expense negatively affects firm sustainable growth, and the industry level fixed assets positively affects firm sustainable growth.

Although the research doesn’t purport to capture all factors that affect AI adoption and firm sustainable growth, and the findings could be further examined by future research, it provides a good understanding and valuable framework within which to develop and test empirical propositions in the related area.

REFERENCES

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, *34*(5), 639-651.

Adner, R., & Helfat, C. E. (2003). Corporate effects and dynamic managerial capabilities. *Strategic management journal*, *24*(10), 1011-1025.

Agrawal, A. K., Gans, J. S., & Goldfarb, A. (2018). *Economic Policy for Artificial Intelligence* (No. w24690). National Bureau of Economic Research.

Ahmadi, H., Nilashi, M., Ibrahim, O., Ramayah, T., Wong, M. W., Alizadeh, M., ... & Almaee, A. (2015). Exploring potential factors in total hospital information system adoption. *Journal of Soft Computing and Decision Support Systems*, *2*(1), 52-59.

Ajjan, H., & Hartshorne, R. (2008). Investigating faculty decisions to adopt Web 2.0 technologies: Theory and empirical tests. *The internet and higher education*, *11*(2), 71-80.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle, [w:] proceedings of the 2nd international symposium on information, bn petrow, f. *Czaki, Akademiai Kiado, Budapest*.

Aleksander, I. (2004). Advances in intelligent information technology: re-branding or progress towards conscious machines? *Journal of Information Technology*, 19(1), 21-27.

Aleksander, I. (2017). Partners of humans: a realistic assessment of the role of robots in the foreseeable future. *Journal of Information Technology*, 32(1), 1-9.

Alsamhi, S. H., Ma, O., & Ansari, M. S. (2018). Artificial Intelligence-Based Techniques for Emerging Robotics Communication: A Survey and Future Perspectives. *arXiv preprint arXiv:1804.09671*.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. PACIS 2018 Proceedings. 37.

Angeles, R., Corritore, C. L., Basu, S. C., & Nath, R. (2001). Success factors for domestic and international electronic data interchange (EDI) implementation for US firms. *International Journal of Information Management*, *21*(5), 329-347.

Anuradha, C. B., & Sharma, P. (2017). Empowering the Future 5G Networks: An AI based Approach. *Telecom Business Review*, *10*(1), 53.

Armstrong, C. P., & Sambamurthy, V. (1999). Information technology assimilation in firms: The influence of senior leadership and IT infrastructures. *Information systems research*, *10*(4), 304-327.

Assael, H. (1984). *Consumer behavior and marketing action*. Kent Pub. Co.

Attewell, P. (1992). Technology diffusion and organizational learning: The case of business computing. *Organization science*, *3*(1), 1-19.

Azadegan, A., & Teich, J. (2010). Effective benchmarking of innovation adoptions: A theoretical framework for e-procurement technologies. *Benchmarking: An International Journal*, *17*(4), 472-490.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science*, *16*(1), 74-94.

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative science quarterly*, 421-458.

Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. *Neural Computing and Applications*, *19*(8), 1165-1195.

Baker, J. (2012). The technology–organization–environment framework. In *Information systems theory* (pp. 231-245). Springer, New York, NY.

Barceló, J. A., & De Almeida, V. M. (2012). Functional analysis from visual and non-visual data. an artificial intelligence approach. *Mediterranean Archaeology and Archaeometry*, *12*(2), 273-321.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), 99-120.

Basarke, C., Berger, C., & Rumpe, B. (2007). Software & systems engineering process and tools for the development of autonomous driving intelligence. *Journal of Aerospace Computing, Information, and Communication*, *4*(12), 1158-1174.

Bay, O. (2018). Generic Telco AI Platforms Will be Driven by Open Source, but it Will be Years Before Widespread Commercial Deployment. *ABI research*. Retrieve from https://www.abiresearch.com/press/generic-telco-ai-platforms-will-be-driven-open-source-it-will-be-years-widespread-commercial-deployment/. Accessed: May 11, 2019.

BBC News. (2016) "Artificial intelligence: Google's AlphaGo beats Go master Lee Se-dol". *BBC News*. 12 March 2016. Retrieve from https://www.bbc.com/news/technology-35785875. Accessed: May 11, 2019.

Beckett, N. & Ge, A. (2017). China publishes the three-year action plan for AI development. CMS, China. Retrieve from https://www.lexology.com/library/detail.aspx?g=89d18185-8c00-4155-8e66-8aa94b4c2515. Accessed: March 5, 2019.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS quarterly*, 169-196.

Bi, Z., Xu, L., & Wang, C. (2014). Internet of things for enterprise systems of modern manufacturing. *IEEE Transactions on Industrial Informatics*, 10(2), 1537-1546.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of cross-cultural psychology*, *1*(3), 185-216.

Buchanan, B. G. (2005). A (very) brief history of artificial intelligence. *Ai Magazine*, *26*(4), 53.

Burnham, K. P., Anderson, D. R., & Huyvaert, K. P. (2011). AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons. *Behavioral ecology and sociobiology*, *65*(1), 23-35.

Butler, D. L., & Sellbom, M. (2002). Barriers to adopting technology. *Educause Quarterly*, *2*(1), 22-28.

CAICT & Gartner. (2018). 2018 World Artificial Intelligence Industry Development Blue Book. 2018 World Artificial Intelligence Conference. Retrieve from

http://www.caict.ac.cn/kxyj/qwfb/bps/201809/P020180918696200669434.pdf. Accessed: March 20, 2019.

Caselli, F., & Coleman, W. J. (2001). Cross-country technology diffusion: The case of computers. *American Economic Review*, *91*(2), 328-335

Castro, A., Richart, M., Baliosian, J., & Grampín, E. (2018, October). Opportunities for AI/ML in Telecommunications Networks. In *Proceedings of the 10th Latin America Networking Conference* (pp. 89-95). ACM.

CCTIME, (2018). "Yiwa" customer service robot has become the largest intelligent interactive system for users worldwide. Retrieve from http://www.cctime.com/html/2018-9-27/1409423.htm. Accessed: March 15, 2019.

Chang, I. C., Hwang, H. G., Hung, M. C., Lin, M. H., & Yen, D. C. (2007). Factors affecting the adoption of electronic signature: Executives' perspective of hospital information department. *Decision Support Systems*, *44*(1), 350-359.

Chang, I. C., Hwang, H. G., Yen, D. C., & Lian, J. W. (2006). Critical factors for adopting PACS in Taiwan: Views of radiology department directors. *Decision Support Systems*, *42*(2), 1042-1053.

Chau, P. Y., & Tam, K. Y. (1997). Factors affecting the adoption of open systems: an exploratory study. *MIS quarterly*, 1-24.

Chen, D. (2016, September). Application of Artificial Intelligence Technology in the Visual Communication Design of Shopping Platform. In *First International Conference on Real Time Intelligent Systems* (pp. 119-126). Springer, Cham.

Chen, H. (2017). Theoretical foundations for cyber-physical systems: a literature review. *Journal of Industrial Integration and Management*, *2*(03), 1750013.

Chen, Y., Chen, H., Gorkhali, A., Lu, Y., Ma, Y., & Li, L. (2016). Big data analytics and big data science: a survey. *Journal of Management Analytics*, *3*(1), 1-42.

Chin, W., & Marcolin, B. (1995). The holistic approach to construct validation in IS research: Examples of the interplay between theory and measurement. In Administrative Sciences Association of Canada-annual Conference- (Vol. 16, pp. 34-43). Administrative Sciences Association of Canada.

Chin, W. W. (1998). Issues and opinion on structural equation modeling. MIS Q. 22, 1998, VII–XVI.

Chin, W. W., & Gopal, A. (1995). Adoption intention in GSS: relative importance of beliefs. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *26*(2-3), 42-64.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic mail emotion/adoption study. *Information Systems Research*, *14(*2), 189-217.

China-tower.com (2018). Company Profile. Retrieve from https://www.china-tower.com/about?nav=01. Accessed: May 15, 2019.

Chong, A.Y.L., Ooi, K.B., Lin, B.S. and Raman, M. (2009) Factors affecting the adoption level of c-commerce: An empirical study, "Journal of Computer Information Systems", Vol. 50, No. 2, pp 13-22

Chong, S., & Bauer, C. (2000). A model of factor influences on Electronic Commerce adoption and diffusion in small-and medium-sized enterprises. *PACIS 2000 Proceedings*, 23.

Chung, H., Park, J., & Lee, S. (2017). Digital forensic approaches for Amazon Alexa ecosystem. *Digital Investigation*, *22*, S15-S25.

Clark, J. (2015). Why 2015 Was a Breakthrough Year in Artificial Intelligence. Retrieve from https://www.bloomberg.com/news/articles/2015-12-08/why-2015-was-a-breakthrough-year-in-artificial-intelligence. Accessed: May 15, 2019.

Co, H. C., Eddy Patuwo, B., & Hu, M. Y. (1998). The human factor in advanced manufacturing technology adoption: An empirical analysis. *International Journal of Operations & Production Management*, *18*(1), 87-106.

Coats, P. K. (1991). A critical look at expert systems for business information applications. *Journal of Information Technology*, *6*(3-4), 208-215.

Creemers, R. (2017). A Next Generation Artificial Intelligence Development Plan, The law and policy of media in China. China Copyright and Media. Retrieve from https://chinacopyrightandmedia.wordpress.com/2017/07/20/a-next-generation-artificial-intelligence-development-plan/. Accessed: May 15, 2019.

Crevier, D. (1993). *AI: the tumultuous history of the search for artificial intelligence*. Basic Books.

Cristiano, J. J., Liker, J. K., & White, C.C. (2001). Key factors in the successful application of quality function deployment (QFD). *IEEE Transactions on Engineering Management*, *48*(1), 81-95.

Dano, m. (2016). AT&T experimenting with artificial intelligence as a 'key enabler' of next-gen wireless. Fierce Wireless. https://www.fiercewireless.com/tech/at-t-experimenting-artificial-intelligence-as-a-key-enabler-next-gen-wireless

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Dedrick, J., & West, J. (2004, January). An exploratory study into open source platform adoption. In *37th Annual Hawaii International Conference on System Sciences, 2004. Proceedings of the* (pp. 10-pp). IEEE.

Deloitte. (2018). China Telecom Industry Insights. Retrieve from https://www2.deloitte.com/cn/en/pages/technology-media-and-telecommunications/articles/china-telecom-industry-insights-aug2018.html. Accessed: May 15, 2019.

Ding,J. (2018). Deciphering China's AI Dream. Retrieve from https://www.fhi.ox.ac.uk/wp-content/uploads/Deciphering_Chinas_AI-Dream.pdf. Accessed: May 15, 2019.

Dutton, T. (2018). An Overview of National AI Strategies. Retrieve from https://medium.com/politics-ai/an-overview-of-national-ai-strategies-2a70ec6edfd. Accessed: May 15, 2019.

Elbanna, A. (2013). Top management support in multiple-project environments: an in-practice view. *European Journal of Information Systems*, *22*(3), 278-294.

El Khatib, M. M., Al-Nakeeb, A., & Ahmed, G. (2019). Integration of Cloud Computing with Artificial Intelligence and Its Impact on Telecom Sector—A Case Study.

Emmelhainz, M. A. (1988). Strategic issues of EDI implementation. *Journal of Business Logistics*, *9*(2), 55.

Ettlie, J. E. (1983). Organizational policy and innovation among suppliers to the food processing sector. *Academy of Management journal*, *26*(1), 27-44.

Faggella,D. (2019). AI in China – Recent History, Strengths and Weaknesses of the Ecosystem. Retrieve from https://emerj.com/ai-market-research/ai-in-china-recent-history-strengths-and-weaknesses-of-the-ecosystem/. Accessed: May 5, 2019.

Falch, M. (1997). Cost and demand characteristics of telecom networks. *Telecom reform: principles, policies and regulatory practices, Technical University of Denmark*, 107-122.

Fast, E., & Horvitz, E. (2017, February). Long-Term Trends in the Public Perception of Artificial Intelligence. In *AAAI* (pp. 963-969).

Feng, S., Xu, L. (2000) Mathematical Modeling of China's State-owned Enterprises' Contract System. *European Journal of Operational Research*, 124, 235-242.

Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European journal of operational research*, *204*(2), 189-198.

Fichman, R. G. (2004). Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *Journal of the association for information systems*, *5*(8), 11.

Fishbein, M., & Ajzen, I. (1975). Intention and Behavior: An introduction to theory and research.

Floyd, S. W., & Lane, P. J. (2000). Strategizing throughout the organization: Managing role conflict in strategic renewal. *Academy of management review*, *25*(1), 154-177.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 39-50.

Fowler, A. (2000). The role of AI-based technology in support of the knowledge management value activity cycle. *The Journal of Strategic Information Systems*, 9(2-3), 107-128.

Fu, Y., Kok, R. A., Dankbaar, B., Ligthart, P. E., & van Riel, A. C. (2018). Factors affecting sustainable process technology adoption: A systematic literature review. *Journal of Cleaner Production*.

Garrison, G., Wakefield, R. L., & Kim, S. (2015). The effects of IT capabilities and delivery model on cloud computing success and firm performance for cloud supported processes and operations. *International Journal of Information Management*, *35*(4), 377-393.

Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the association for Information Systems*, *1*(1), 8.

Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the association for information systems*, *4*(1), 7.

George, D. (2011). *SPSS for windows step by step: A simple study guide and reference, 17.0 update, 10/e*. Pearson Education India.

GG-robot, (2016). China Mobile's intelligent customer service "Yiwa": on the line to save costs 110 million yuan. Retrieve from https://www.gg-robot.com/asdisp2-65b095fb-59459-.html. Accessed: May 15, 2019.

Gibbs, J. L., & Kraemer, K. L. (2004). A cross-country investigation of the determinants of scope of e-commerce use: an institutional approach. *Electronic markets*, *14*(2), 124-137.

Goldberg, D. E., & Holland, J. H. (1988). Genetic algorithms and machine learning. *Machine learning*, *3*(2), 95-99.

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1). Cambridge: MIT press.

Greenhalgh, T., Robert, G., Macfarlane, F., Bate, P., & Kyriakidou, O. (2004). Diffusion of innovations in service organizations: systematic review and recommendations. *The Milbank Quarterly*, *82*(4), 581-629.

Grover, V., Jeong, S. R., Kettinger, W. J., & Teng, J. T. (1995). The implementation of business process reengineering. *Journal of Management Information Systems*, *12*(1), 109-144.

Gruber, H. (1999). An investment view of mobile telecommunications in the European Union. *Telecommunications Policy*, *23*(7-8), 521-538.

Hair, J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Thousand Oaks: Sage.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). Multivariate data analysis (Vol. 5, No. 3, pp. 207-219).

Hage, J., & Dewar, R. (1973). Elite values versus organizational structure in predicting innovation. *Administrative science quarterly*, 279-290.

Hall, D.W. & Pesenti, J. (2017). Growing the artificial intelligence industry in the UK. Retrieve from https://www.gov.uk/government/publications/growing-the-artificial-intelligence-industry-in-the-uk. Accessed: May 5, 2019.

Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. *Metabolism*, *69*, S36-S40.

Han, H. S., Lee, J. N., & Seo, Y. W. (2008). Analyzing the impact of a firm's capability on outsourcing success: A process perspective. *Information & Management*, *45*(1), 31-42.

Hannan, T. H., & McDowell, J. M. (1984). The determinants of technology adoption: The case of the banking firm. *The RAND Journal of Economics*, 328-335.

Hao, H., Padman, R., Sun, B., & Telang, R. (2018). Quantifying the impact of social influence on the information technology implementation process by physicians: A hierarchical Bayesian learning approach. *Information Systems Research*, *29*(1), 25-41.

Hartono, G. C., & Utami, S. R. (2016). The Comparison of Sustainable Growth Rate, Firm‟ s Performance and Value among the firms in Sri Kehati Index and IDX30 Index in Indonesia Stock Exchange. *International Journal of Advanced Research in Management and Social Sciences*, *5*(5), 68-81.

Hauptmann, A. G., Witbrock, M. J., & Christel, M. G. (1997, March). Artificial intelligence techniques in the interface to a digital video library. In *CHI'97 Extended Abstracts on Human Factors in Computing Systems* (pp. 2-3). ACM.

He, Z. (2015). Rivalry, market structure and innovation: The case of mobile banking. *Review of Industrial Organization*, *47*(2), 219-242.

House, R., Javidan, M., Hanges, P., & Dorfman, P. (2002). Understanding cultures and implicit leadership theories across the globe: an introduction to project GLOBE. *Journal of world business*, *37*(1), 3-10.

Hsu, P. F., Kraemer, K. L., & Dunkle, D. (2006). Determinants of e-business use in US firms. *International Journal of Electronic Commerce*, *10*(4), 9-45.

Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: theory and applications. *Neurocomputing*, *70*(1-3), 489-501.

Huang, Z., & Palvia, P. (2001). ERP implementation issues in advanced and developing countries. *Business process management journal*, *7*(3), 276-284.

Huebner, R. A. (2017). *A Quantitative Analysis of Organizational Factors that Relate to Data Mining Success* (Doctoral dissertation, Capella University).

Hung, S. Y., Huang, W. M., Yen, D. C., Chang, S. I., & Lu, C. C. (2016). Effect of information service competence and contextual factors on the effectiveness of strategic information systems planning in Hospitals. *Journal of Global Information Management (JGIM)*, *24*(1), 14-36.

Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS quarterly*, 465-485.

IEEE. (2017). IEEE Releases Ethically Aligned Design, Version 2 to show "Ethics in Action" for the Development of Autonomous and Intelligent Systems (A/IS), News & Events: Press Releases. IEEE Standards Association. https://standards.ieee.org/news/2017/ead_v2.html#

Ifinedo, P. (2011). An empirical analysis of factors influencing Internet/e-business technologies adoption by SMEs in Canada. *International Journal of Information Technology & Decision Making*, *10*(04), 731-766.

Intakhan, P. (2014). Direct & indirect effects of top management support on abc implementation success: Evidence from iso 9000 certified companies in Thailand. *Procedia-Social and Behavioral Sciences*, *164*, 458-470.

Ishaya, T., & Folarin, M. (2012). A service oriented approach to Business Intelligence in Telecoms industry. *Telematics and Informatics*, *29*(3), 273-285.

ITI. (2017). Artificial Intelligence Policy Principles https://www.itic.org/dotAsset/50ed66d5-404d-40bb-a8ae-9eeeef55aa76.pdf

Jayaraman, V., & Srivastava, R. (1996). Expert systems in production and operations management: current applications and future prospects. *International Journal of Operations & Production Management*, *16*(12), 27-44.

Kasemsap, K. (2017). Artificial intelligence: Current issues and applications. In *Handbook of research on manufacturing process modeling and optimization strategies* (pp. 454-474). IGI Global.

Kettinger, W. J., Li, Y., Davis, J. M., & Kettinger, L. (2015). The roles of psychological climate, information management capabilities, and IT support on knowledge-sharing: an MOA perspective. *European Journal of Information Systems*, *24*(1), 59-75.

Kline, P. (2013). *Handbook of psychological testing*. Routledge.

Kline, R. (1998). Principles and practice of structural equation modeling. New York, NY:The Guilford Press.

Kiernan, N.E., Kiernan, M., Oyler, M.A., & Gilles, C. (2005). Is a web survey as effective as a mail survey? A field experiment among computer users. *American Journal of Evaluation, 26*(2), 245-252.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & management*, *43*(6), 740-755.

Kor, Y. Y., & Mesko, A. (2013). Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic. *Strategic management journal*, *34*(2), 233-244.

Kosaroglu, M., & Hunt, R. A. (2009). New product development projects and project manager skill sets in the telecommunications industry. *International Journal of Managing Projects in Business*, *2*(2), 308-317.

Kouziokas, G. N. (2017). The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment. *Transportation research procedia*, *24*, 467-473.

Kuan, K. K., & Chau, P. Y. (2001). A perception-based model for EDI adoption in small businesses using a technology–organization–environment framework. *Information & management*, *38*(8), 507-521.

Kumar, A., Irsoy, O., Ondruska, P., Iyyer, M., Bradbury, J., Gulrajani, I., ... & Socher, R. (2016, June). Ask me anything: Dynamic memory networks for natural language processing. In *International Conference on Machine Learning* (pp. 1378-1387).

Kusiak, A. (2017). Smart manufacturing must embrace big data. *Nature News*, *544*(7648), 23.

Kwon, T. H., & Zmud, R. W. (1987, April). Unifying the fragmented models of information systems implementation. In *Critical issues in information systems research* (pp. 227-251). John Wiley & Sons, Inc.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, *14*(1), 21-38.

Laitila, T. (2018). The Role of Managerial Capabilities and Organizational Culture in Corporate Venturing: The Case of a Successful Corporate Spin-off.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature*, *521*(7553), 436.

Lee, D. T. (1988). Expert decision-support systems for decision-making. *Journal of Information Technology*, *3*(2), 85-94.

Lee, M. C. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic commerce research and applications*, *8*(3), 130-141.

Lemke, H. U. (2003). PACS developments in Europe. *Computerized Medical Imaging and Graphics*, *27*(2-3), 111-120.

Li, B. H., Hou, B. C., Yu, W. T., Lu, X. B., & Yang, C. W. (2017). Applications of artificial intelligence in intelligent manufacturing: a review. *Frontiers of Information Technology & Electronic Engineering*, *18*(1), 86-96.

Li, J., Cheng, H., Guo, H., & Qiu, S. (2018). Correction to: Survey on Artificial Intelligence for Vehicles. *Automotive Innovation*, 1-1.

Li, L. (2018). China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0". *Technological Forecasting and Social Change*, 135, 66-74.

Li, L., & Zhou, H. (2013). Manufacturing practices in China. *International Journal of Production Economics*, 146(1), 1-3.

Li, R., Zhao, Z., Zhou, X., Ding, G., Chen, Y., Wang, Z., & Zhang, H. (2017). Intelligent 5G: When cellular networks meet artificial intelligence. *IEEE Wireless Communications*, *24*(5), 175-183.

Li, S., Xu, L.D., & Zhao, S. (2018). 5G Internet of Things: A survey. *Journal of Industrial Information Integration*, online published.

Li, Y. H. (2008, September). An empirical investigation on the determinants of e-procurement adoption in Chinese manufacturing enterprises. In *Management Science and Engineering, 2008. ICMSE 2008. 15th Annual Conference Proceedings., International Conference on* (pp. 32-37). IEEE.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS quarterly*, 59-87.

Liao, S. H. (2005). Expert system methodologies and applications—a decade review from 1995 to 2004. *Expert systems with applications*, *28*(1), 93-103.

Lim, K. H. (2009). Knowledge management systems diffusion in Chinese enterprises: A multistage approach using the technology-organization-environment framework. *Journal of Global Information Management (JGIM)*, *17*(1), 70-84.

Lin, H. F., & Lin, S. M. (2008). Determinants of e-business diffusion: A test of the technology diffusion perspective. *Technovation*, *28*(3), 135-145.

Lippert, S. K., & Govindarajulu, C. (2006). Technological, organizational, and environmental antecedents to web services adoption. *Communications of the IIMA*, *6*(1), 14.

Liu, M. (2008, October). Determinants of e-commerce development: An empirical study by firms in shaanxi, china. In *Wireless Communications, Networking and Mobile Computing, 2008. WiCOM'08. 4th International Conference on* (pp. 1-4). IEEE.

Livne, G., Simpson, A., & Talmor, E. (2008). Do customer acquisition cost, call usage and customer retention matter in the wireless industry?

Lovely, M., & Popp, D. (2017). Trade, technology, and the environment: Does access to technology promote environmental regulation? In *International Economic Integration and Domestic Performance* (pp. 169-188).

Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial management & data systems*, *111*(7), 1006-1023.

Lyytinen, K., & Damsgaard, J. (2011). Inter-organizational information systems adoption–a configuration analysis approach. *European journal of information systems*, *20*(5), 496-509.

Macleish, K. J. (1988). Mapping the integration of artificial intelligence into telecommunications. *IEEE journal on selected areas in communications*, *6*(5), 892-898.

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., & Beardsley, G. (1977). Social and private rates of return from industrial innovations. *The Quarterly Journal of Economics*, *91*(2), 221-240.

Markram, H. (2012). The human brain project. *Scientific American*, *306*(6), 50-55.

Mazerolle, M. J. (2006). Improving data analysis in herpetology: using Akaike's Information Criterion (AIC) to assess the strength of biological hypotheses. *Amphibia Reptilia*, *27*(2), 169-180.

McCarthy, J. (1960). *Programs with common sense* (pp. 300-307). RLE and MIT computation center.

McCloughan, P., & Lyons, S. (2006). Accounting for ARPU: New evidence from international panel data. *Telecommunications Policy*, *30*(10-11), 521-532.

McCorduck, P. (2009). *Machines who think: A personal inquiry into the history and prospects of artificial intelligence*. AK Peters/CRC Press.

McDermott, J. (1982). R1: A rule-based configurer of computer systems. *Artificial intelligence*, *19*(1), 39-88.

Meek, T., Barham, H., Beltaif, N., Kaadoor, A., & Akhter, T. (2016). Managing the ethical and risk implications of rapid advances in artificial intelligence: A literature review. In *Portland*

International Conference on Management of Engineering and Technology: Technology Management for Social Innovation, Proceedings (p. 682).

Meiring, G. A. M., & Myburgh, H. C. (2015). A review of intelligent driving style analysis systems and related artificial intelligence algorithms. *Sensors*, *15*(12), 30653-30682.

METZ, C. (2017). Alphago's designers explore new AI after winning big in China. Business. Retrieve from https://www.wired.com/2017/05/win-china-alphagos-designers-explore-new-ai/. Accessed: May 5, 2019.

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How information management capability influences firm performance. *MIS quarterly*, *35*(1), 237.

Mitter, S. (2018). 3 ways in which AI will be integrated in our daily lives in the 2020s. Retrieve from https://yourstory.com/2018/01/3-ways-ai-will-integrated-daily-lives-2020s. Accessed: May 5, 2019.

Mogel, G. T. (2003). The role of the Department of Defense in PACS and telemedicine research and development. *Computerized medical imaging and graphics*, *27*(2-3), 129-135.

Mohammadi, H. (2015). Factors affecting the e-learning outcomes: An integration of TAM and IS success model. *Telematics and Informatics*, *32*(4), 701-719.

Morton, S. MS (Ed). (1991). The corporation of the 1990s: Information technology and organizational transformation.

Muller, C., Magill, E. H., Prosser, P., & Smith, D. G. (1993). Artificial intelligence in telecommunications. In *Global Telecommunications Conference, 1993, including a*

Communications Theory Mini-Conference. Technical Program Conference Record, IEEE in Houston. GLOBECOM'93., IEEE (pp. 883-887). IEEE.

Müller, R., & Jugdev, K. (2012). Critical success factors in projects: Pinto, Slevin, and Prescott–the elucidation of project success. *International Journal of Managing Projects in Business*, *5*(4), 757-775.

Murphy, J. (2018). Artificial Intelligence, Rationality, and the World Wide Web. *IEEE Intelligent Systems*, *33*(1), 98-103.

Murphy, C. (2019). Sustainable Growth Rate – SGR Definition. Retrieve from https://www.investopedia.com/terms/s/sustainablegrowthrate.asp. Accessed: June 6, 2019.

Nah, F. F. H., Lau, J. L. S., & Kuang, J. (2001). Critical factors for successful implementation of enterprise systems. *Business process management journal*, *7*(3), 285-296.

Nakayama, M. (2003). An assessment of EDI use and other channel communications on trading behavior and trading partner knowledge. *Information & Management*, *40*(6), 563-580.

NCBC, (2018). China Tower raises $6.9 billion in world's largest IPO in two years, sources say. Retrieve from https://www.cnbc.com/2018/08/01/china-tower-raises-6point9-billion-in-largest-ipo-in-two-years-sources.html. Accessed: May 5, 2019.

Neokosmidis, I., Rokkas, T., Xydias, D., Albanese, A., Siddiqui, M. S., Colman-Meixner, C., & Simeonidou, D. (2018, May). Are 5G Networks and the Neutral Host Model the Solution to the Shrinking Telecom Market. In *IFIP International Conference on Artificial Intelligence Applications and Innovations* (pp. 70-77). Springer, Cham.

Nikolaeva, R. (2006). E-commerce adoption in the retail sector: empirical insights. *International Journal of Retail & Distribution Management*, *34*(4/5), 369-387.

Nilsson, N. J. (2014). *Principles of artificial intelligence*. Morgan Kaufmann.

NITRD. (2016). The National Artificial Intelligence Research and Development Strategic Plan. Retrieve from https://www.nitrd.gov/news/national_ai_rd_strategic_plan.aspx. Accessed: May 5, 2019.

Nokia. (2018). Nokia and China Mobile to set up joint AI*5G lab for further research using artificial intelligence and machine learning in 5G networks. Nokia. Retrieve from https://www.nokia.com/en_int/news/releases/2018/07/06/nokia-and-china-mobile-to-set-up-joint-ai5g-lab-for-further-research-using-artificial-intelligence-and-machine-learning-in-5g-networks. Accessed: May 5, 2019.

Nolfi, S., Bongard, J., Husbands, P., & Floreano, D. (2016). Evolutionary robotics. In *Springer Handbook of Robotics* (pp. 2035-2068). Springer, Cham.

Norvig, P. (2012). Artificial intelligence: A new future. *New Scientist*, *216*(2889), vi-vii.

Nunnally, J. C., & Bernstein, I. H. (1967). *Psychometric theory* (Vol. 226). New York: McGraw-Hill.

Oliveira, T., & Martins, M. F. (2008, July). A Comparison of Web Site Adoption in Small and Large Portuguese Firms. In *ICE-B* (pp. 370-377).

Oliveira, T., & Martins, M. F. (2010). Understanding e-business adoption across industries in European countries. *Industrial Management & Data Systems*, *110*(9), 1337-1354.

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Electronic Journal of Information Systems Evaluation*, *14*(1), 110.

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors. *Information & Management*, *51*(5), 497-510.

Orange. (2018). Djingo, your multi-service virtual assistant. Orange. Retrieve from https://www.orange.com/en/Human-Inside/Shaping-tomorrow-s-world/SH2017/Djingo-your-multi-service-virtual-assistant. Accessed: May 15, 2019.

Osborne, C. (2019). Enterprise adoption of AI has grown 270 percent over the past four years. Retrieve from https://www.zdnet.com/article/enterprise-adoption-of-ai-has-grown-270-percent-over-the-past-four-years/. Accessed: May 5, 2019.

Oyelude, A. A. (2017). What's trending in libraries from the internet cybersphere–artificial intelligence and other emerging technologies. *Library Hi Tech News*, *34*(2), 11-12.

Pan, M. J., & Jang, W. Y. (2008). Determinants of the adoption of enterprise resource planning within the technology-organization-environment framework: Taiwan's communications industry. *Journal of Computer information systems*, *48*(3), 94-102.

Pannu, A. (2015). Artificial intelligence and its application in different areas. *Artificial Intelligence*, *4*(10), 79-84.

Parker, C. M., & Swatman, P. M. (1995). Educating tomorrow′ s managers for telecommunications and EDI: a cross-cultural experience. *Information Technology & People*, *8*(2), 58-79.

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS quarterly*, 105-136.

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage.

Prendergast, K. A., & Winston, P. H. (1984). *The AI business: the commercial uses of artificial intelligence*. Cambridge, Mass.: MIT Press.

Proenza, F. J. (2001). Telecenter sustainability: Myths and opportunities. *The Journal of Development Communication*, *12*(2), 94-109.

Qi, J., Wu, F., Li, L., & Shu, H. (2007). Artificial intelligence applications in the telecommunications industry. *Expert Systems*, *24*(4), 271-291.

Qiu, C. (2018). Application of Artificial Intelligence Technology in GIS. Journal of advanced oxidation technologies, *21*(2).

Quaddus, M., & Xu, J. (2005). Adoption and diffusion of knowledge management systems: field studies of factors and variables. *Knowledge-based systems*, *18*(2-3), 107-115.

Rao, S. S., Nahm, A., Shi, Z., Deng, X., & Syamil, A. (1999). Artificial intelligence and expert systems applications in new product development—a survey. *Journal of Intelligent Manufacturing*, *10*(3-4), 231-244.

Ravichandran, T., & Lertwongsatien, C. (2005). Effect of information systems resources and capabilities on firm performance: A resource-based perspective. *Journal of management information systems*, *21*(4), 237-276.

Raymond, L. (1990). Organizational context and information systems success: a contingency approach. *Journal of Management Information Systems*, *6*(4), 5-20.

Reich, B. H., & Benbasat, I. (1990). An empirical investigation of factors influencing the success of customer-oriented strategic systems. *Information Systems Research*, *1*(3), 325-347.

Rich, E., & Knight, K. (1991). *Artificial intelligence*. Tata McGraw-Hill.

Rich, E., & Knight, K. (2009). *Artificial intelligence Third Edition*. McGraw-Hill, New.

Rogers, E. M. (1995). Diffusion of Innovation. 4th. *New York: The Free* Press.

Rogers, E. M. (2003). The diffusion of innovation 5th edition.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited.

Sanders, G. L., & Courtney, J. F. (1985). A field study of organizational factors influencing DSS success. *MIS quarterly*, 77-93.

Schmidhuber, J. (2007). Celebrating 75 years of AI-history and outlook: the next 25 years.

Scott, W. R. (2008). *Institutions and organizations: Ideas and interests*. Sage.

Scott, W. R., & Christensen, S. (1995). *The institutional construction of organizations: International and longitudinal studies*. Sage Publications, Inc.

Sehgal, R. R., Agarwal, S., & Rai, G. (2018, June). Interactive Voice Response using Sentiment Analysis in Automatic Speech Recognition Systems. In *2018 International Conference on Advances in Computing and Communication Engineering (ICACCE)* (pp. 213-218). IEEE.

Semenov, V. P., Chernokulsky, V. V., & Razmochaeva, N. V. (2017, October). Research of artificial intelligence in the retail management problems. In *Control in Technical Systems (CTS), 2017 IEEE II International Conference on* (pp. 333-336). IEEE.

Sennaar, K. (2018). Telecom Machine Learning Applications – Comparing AT&T, Verizon, Comcast and More. https://www.techemergence.com/telecom-machine-learning-applications/

Seshadri, V. (1996). Guest Editor. AI in telecommunications. *IEEE Intelligent Systems*, (1), 36.

Shapiro, E. Y. (1983). The fifth-generation project—a trip report. *Communications of the ACM*, *26*(9), 637-641.

Shenoy, R. P. (1985). Artificial intelligence--the emerging technology. *Defence science journal. Delhi*, *35*(2), 135-149.

Siciliano, B., & Khatib, O. (Eds.). (2016). *Springer handbook of robotics*. Springer.

Simou, P., Tiligadis, K., & Alexiou, A. (2013, September). Exploring artificial intelligence utilizing BioArt. In *IFIP International Conference on Artificial Intelligence Applications and Innovations* (pp. 687-692). Springer, Berlin, Heidelberg.

Smith, M. J. (2018). Getting value from artificial intelligence in agriculture, over the next 10+ years.

Steiger, D. M. (1998). Enhancing user understanding in a decision support system: a theoretical basis and framework. Journal of Management Information Systems, 15(2), 199-220.

Stoica, M., Miller, D. W., & Stotlar, D. (2005). New technology adoption, business strategy and government involvement: The case of mobile commerce. *Journal of Nonprofit & Public Sector Marketing*, *13*(1-2), 213-232.

Sulaiman, H., & Wickramasinghe, N. (2014). Assimilating Healthcare Information Systems in a Malaysian Hospital. *CAIS*, *34*, 77.

Sumner, M. (2000). Risk factors in enterprise-wide/ERP projects. *Journal of information technology*, *15*(4), 317-327.

Sun Yin, H. H., Langenheldt, K., Harlev, M., Mukkamala, R. R., & Vatrapu, R. (2019). Regulating Cryptocurrencies: A Supervised Machine Learning Approach to De-Anonymizing the Bitcoin Blockchain. *Journal of Management Information Systems*, 36(1), 37-73.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, *69*, 135-146.

Syeda, S. H. (2018). *An Exploratory Study to Identify Critical Success Factors of Agile Systems Engineering* (Doctoral dissertation, The George Washington University).

Symonds, M. R., & Moussalli, A. (2011). A brief guide to model selection, multimodel inference and model averaging in behavioural ecology using Akaike's information criterion. *Behavioral Ecology and Sociobiology*, *65*(1), 13-21.

Tang, X., & Xia, X. (2016). An Analysis of Chinese 4G Telecom Market. *Journal of Economics*, *4*(4), 23-33.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533.

Teo, T. S., Ranganathan, C., & Dhaliwal, J. (2006). Key dimensions of inhibitors for the deployment of web-based business-to-business electronic commerce. *IEEE Transactions on engineering Management*, *53*(3), 395-411.

Thiesse, F., Staake, T., Schmitt, P., & Fleisch, E. (2011). The rise of the “next-generation bar code”: an international RFID adoption study. *Supply Chain Management: An International Journal*, *16*(5), 328-345.

Thong, J. Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of management information systems*, *15*(4), 187-214.

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education*, *26*(2), 701-712.

Tornatzky, L. and Fleischer, M. (1990) The process of technology innovation, Lexington, MA, Lexington Books.

Tractica. (2018). Artificial Intelligence for Telecommunications Applications. Retrieve from https://www.tractica.com/research/artificial-intelligence-for-telecommunications-applications/. Accessed: May 5, 2019.

Venkatesh, V., Bala, H., & Sambamurthy, V. (2016). Implementation of an information and communication technology in a developing country: a multimethod longitudinal study in a bank in India. *Information Systems Research*, *27*(3), 558-579.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Vodafone. (2017). Meet TOBi – the first live chatbot in UK telecoms. Retrieve from http://labs.vodafone.co.uk/case-studies/tobi. Accessed: May 15, 2019.

Walczak, S. (2018). Artificial Neural Networks and other AI Applications for Business Management Decision Support. In *Intelligent Systems: Concepts, Methodologies, Tools, and Applications* (pp. 2047-2071). IGI Global.

Wallace, L. G., & Sheetz, S. D. (2014). The adoption of software measures: A technology acceptance model (TAM) perspective. *Information & Management*, *51*(2), 249-259.

Wang, E. T., Tai, J. C., & Grover, V. (2013). Examining the relational benefits of improved interfirm information processing capability in buyer-supplier dyads. *MIS quarterly*, 149-173.

Wang, P., Chaudhry, S., & Li, L. (2016). Introduction: advances in IoT research and applications. *Internet Research*, 26(2).

Wang, Y. M., Wang, Y. S., & Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. *Technological forecasting and social change*, *77*(5), 803-815.

Wang, Z. C., & Du, P. (2010, September). A practical technology of combining genetic programming with artificial intelligence. In *Computational Intelligence and Natural Computing Proceedings (CINC), 2010 Second International Conference on* (Vol. 2, pp. 300-303). IEEE.

Waterman, D.A. (1986). A Guide to Expert Systems, Addison-Wesley, Reading, MA,

Wen, K. W., & Chen, Y. (2010). E-business value creation in Small and Medium Enterprises: a US study using the TOE framework. *International Journal of Electronic Business*, *8*(1), 80-100.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic management journal*, *5*(2), 171-180.

Willis, R. G., & Sullivan, K. H. (1984). CIMS in perspective-costs, benefits, timing, payback periods are outlined. *Industrial Engineering*, *16*(2), 28.

Wixom, B. H., & Watson, H. J. (2001). An empirical investigation of the factors affecting data warehousing success. *MIS quarterly*, 17-41.

Wojcik, D., & Camilleri, J. (2015). 'Capitalist tools in socialist hands'? China Mobile in global financial networks. *Transactions of the Institute of British Geographers*, *40*(4), 464-478.

Wu, I. (2015). Electricity and telecom regulation: China in context.

Wu, J. H., Wang, S. C., & Lin, L. M. (2007). Mobile computing acceptance factors in the healthcare industry: A structural equation model. *International journal of medical informatics*, *76*(1), 66-77.

Wu, Y., Cegielski, C. G., Hazen, B. T., & Hall, D. J. (2013). Cloud computing in support of supply chain information system infrastructure: understanding when to go to the cloud. *Journal of Supply Chain Management*, *49*(3), 25-41.

Xinhua. (2016). Baidu, China Unicom partner to promote artificial intelligence. Global Times. Retrieve from http://www.globaltimes.cn/content/1015672.shtml. Accessed: May 5, 2019.

Xinhua net. (2016). China Mobile launches intelligent robot customer service. "Yiwa". Xinhua net. Retrieve from http://www.xinhuanet.com/2016-12/20/c_135919778.htm. Accessed: May 5, 2019.

Xu, B., Xu, L., Cai, H., Jiang, L., Luo, Y., & Gu, Y. (2017) The Design of an M-Health Monitoring System based on a Cloud Computing Platform. *Enterprise Information Systems*, 11(1), 17-36. DOI: 10.1080/17517575.2015.1053416

Xu, K., Wang, X., Wei, W., Song, H., & Mao, B. (2016). Toward software defined smart home. *IEEE Communications Magazine*, *54*(5), 116-122.

Xu, L. (2011) Enterprise Systems: State-of-the-Art and Future Trends. *IEEE Transactions on Industrial Informatics*, 7(4), 630-640.

Xu, L. D., & Duan, L. (2018). Big data for cyber physical systems in industry 4.0: a survey. *Enterprise Information Systems*, 1-22.

Xu, L., He, W., & Li, S. (2014). Internet of things in industries: A survey. *IEEE Transactions on industrial informatics*, 10(4), 2233-2243.

Xu, L., Liang, N., Gao, Q. (2008) An Integrated Approach for Agricultural Ecosystem Management. *IEEE Transactions on Systems, Man, and Cybernetics*, Part C (Applications and Reviews), 38(4), 590-599.

Xu, L. D., Xu, E. L., & Li, L. (2018). Industry 4.0: state of the art and future trends. *International Journal of Production Research*, 56(8), 2941-2962.

Xu, X., Thong, J. Y., & Tam, K. Y. (2017). Winning back technology disadopters: testing a technology readoption model in the context of mobile internet services. *Journal of Management Information Systems*, *34*(1), 102-140.

Yahoo.com (2018). Company profile. Retrieve from https://finance.yahoo.com/quote/CHA/profile?p=CHA;

https://finance.yahoo.com/quote/CHL/profile?p=CHL&.tsrc=fin-srch; https://finance.yahoo.com/quote/CHU/profile?p=CHU&.tsrc=fin-srch; https://finance.yahoo.com/quote/CHWRF/profile?p=CHWRF. Accessed: May 25, 2019.

Yang, Z., & Kankanhalli, A. (2013, June). Innovation in government services: The case of open data. In *International Working Conference on Transfer and Diffusion of IT* (pp. 644-651). Springer, Berlin, Heidelberg.

Yang, Z., Kankanhalli, A., Ng, B. Y., & Lim, J. T. Y. (2013). Analyzing the enabling factors for the organizational decision to adopt healthcare information systems. *Decision Support Systems*, *55*(3), 764-776.

Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. *Computers in Human Behavior*, *45*, 254-264.

Yiu, C. S., Grant, K., & Edgar, D. (2007). Factors affecting the adoption of Internet Banking in Hong Kong—implications for the banking sector. *International journal of information management*, *27*(5), 336-351.

Zang, Y., Zhang, F., Di, C. A., & Zhu, D. (2015). Advances of flexible pressure sensors toward artificial intelligence and health care applications. *Materials Horizons*, *2*(2), 140-156.

Zhang, Y., & Lorenz, P. (2018). AI for Network Traffic Control. *IEEE Network*, *32*(6), 6-7.

Zhou, M. Y., & Lawless, W. F. (2015). An Overview of Artificial Intelligence in Education. In *Encyclopedia of Information Science and Technology, Third Edition* (pp. 2445-2452). IGI Global.

Zhu, G. (2018). SoftCOM AI: Hard on the competition with zero faults. Huawei. Retrieve from https://www.huawei.com/us/about-huawei/publications/communicate/85/softcom-ai-hard-on-the-competition. Accessed: May 5, 2019.

Zhu, K., Kraemer, K., & Xu, S. (2003). Electronic business adoption by European firms: a cross-country assessment of the facilitators and inhibitors. *European Journal of Information Systems*, *12*(4), 251-268.

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry. *Information systems research*, *16*(1), 61-84.

Zhu, K., Dong, S., Xu, S. X., & Kraemer, K. L. (2006). Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies. *European journal of information systems*, *15*(6), 601-616.

Zou, X. (2015). Innovation and scientific breakthroughs in artificial intelligence methods. In *Management, Information and Educational Engineering* (pp. 929-932). CRC Press.

APPENDICES

Appendix A. Approval Letter

OLD DOMINION UNIVERSITY

OFFICE OF THE VICE PRESIDENT FOR RESEARCH

aaalac INTERNATIONAL PROUDLY, AN AAALAC ACCREDITED PROGRAM

Physical Address
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DATE:	January 9, 2019
TO:	Hong Chen
FROM:	Old Dominion University Business Human Subjects Review Committee
PROJECT TITLE:	[1366114-2] Success factors for Artificial Intelligence adoption
REFERENCE #:	
SUBMISSION TYPE:	Revision
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	January 9, 2019
REVIEW CATEGORY:	Exemption category # *[6.2]*

Thank you for your submission of Revision materials for this project. The Old Dominion University Business Human Subjects Review Committee has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will retain a copy of this correspondence within our records.

If you have any questions, please contact Kenneth Yung at (757) 683-4048 or kyung@odu.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within Old Dominion University Business Human Subjects Review Committee's records.

Appendix B. Survey (English version)

A survey on organizational success factors for Artificial Intelligence (AI) adoption

This survey explores the organizational critical success factors for AI adoption. It is intended for organizations that offer or plan to adopt AI technologies or applications. This survey is primarily intended for research use and any information you provide in this study will be kept and will not be disclosed. It takes about 20 minutes to complete this survey. Thank you for taking the time to complete this important questionnaire.

Background introduction

AI is a technical science that studies and develops theories, methods, techniques, and applications that simulate, extend, and expand human intelligence. AI mainly includes the following different fields:

1.Machine vision technology. Machine vision refers to the use of cameras and computers to replace the human eye's recognition, tracking and measurement of objects. It has been widely used in video surveillance, autonomous driving, vehicle/face recognition, medical image analysis, archeology, and aerial remote sensing measurement.

2. Expert System. Expert System is a computer system that includes the knowledge base, the inference engine and the user interface. It has been widely used in in the process of decision support and problem solving.

3. Natural language understanding. Natural language understanding includes natural language processing (NLP), speech recognition and speech synthesis. NLP uses and supports text analytics by facilitating the understanding of sentence structure and meaning, sentiment, and intent through statistical and machine learning methods. it is used in machine translation, subtitle generation, text

semantic comparison. Speech recognition and speech synthesis are used in interactive voice response systems, voice assistant, and mobile applications.

4. **Machine learning.** Machine learning is the most powerful tool behind **AI**. It provides algorithms, APIs, development and training toolkits, data, as well as computing power to design, train, and deploy models into applications, processes, and other machines. It is used in fingerprint recognition, face detection, and object detection.

5. Deep learning. Deep learning, also known as deep neural network, is a special type of machine learning that enables computers to learn from experience and understand the world based on hierarchy of concepts. Deep learning is good at identifying unstructured data such as images, sounds, videos, texts, etc., and can be used in almost all popular AI applications.

The most several popular AI applications in telecom companies:

1.Customer service chatbots. It refers to providing 7×24 hours of intelligent response service to users in human-computer interaction mode. For example, China Mobile launched its customer service bot 'Yiwa', which has more than 200 million interactions with customers in a single month. In addition, through artificial intelligence technology such as speech semantic analysis, the quality inspection department can detect sensitive complaint keywords in time, deal with customer complaints and dissatisfaction in a timely manner; and can also predict customer satisfaction by combining sentiment analysis technology to improve customer service quality and optimize customer experience.

2. **Speech and voice services for customers**. Voice Assistant can provide personalized service to customers. Customers use voice and text to control voice assistants to navigate TV, make calls or access other services. For example, Orange, the French mobile telco, has released its new product,

an AI-powered virtual assistant called Djingo, which can be controlled by voice or text. It offers an easy and intuitive way for customers to navigate Orange TV, manage connected home devices, make a call or access lots of other services.

3.Network operations monitoring and management. The application of AI technology makes the network more intelligent, and can realize intelligent control of network and service, such as network intelligent operation and maintenance and intelligent optimization, and quickly intercept malicious behavior, prevent attacks, and maintain network security through machine learning.

4. Generic telco AI platforms. The AI platform is geared to various scenarios such as smart connection, smart decision-making, and smart service to better support and serve the AI industry and the intelligent transformation of various industries. For example, China Mobile's Ninth Heaven platform.

In short, artificial intelligence is a strategic technology that leads the future and is the core driving force for a new round of informatization development and industrial competition in the world. The application and development of AI in the telecom industry is in its infancy. The AI in the following questionnaires includes the above research fields and industry applications. If you are not familiar with AI, for ease of understanding and thinking, you can imagine an application that your company is ready to implement AI, such as intelligent customer service robots, intelligent network self-diagnosis and optimization, voice assistants, and customer data mining and analysis, etc.

Please indicate your response to the following items on a scale of 1 to 7, where 1= Strongly Disagree, 4=Neutral, and 7=Strongly Agree. There are no right or wrong answers, so please only state your opinion.

Government involvement

1. The specification and stability of government policies are beneficial for business operation.

   1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

2. The government can provide financial aid.

   1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

3. The government can supply related information.

   1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

4. We should maintain good relationship with local government.

   1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

5. The government support and help are very important for us to innovate.

   1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Market factor /uncertainty

6. There is a trend in our principal industry to utilize more AI technologies for business development and applications.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

7. AI has broad application prospects in our principal industry.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

8. Only innovative technologies can help our company to provide perfect products and services to meet the growing personalized needs of consumers.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

9. AI can help our company to gain competitiveness.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Competitive pressure

10. The rate of innovation of new operating processes and new products or services in our principal industry has increased dramatically.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

11. An industry moves to utilize the AI technologies for innovation would put pressure on our company to do the same.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

12. There is tough price competition in our industry.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

13. There is tough competition on product/service quality.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Vendor partnership

14. We have had no difficulty in obtaining assistance from our vendors/partners.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

15. Our vendors/partners are trustworthy.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

16. Vendors make decisions beneficial to our organization.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

17. We have very close relationships with vendors/partners.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

18. Our vendors/partners are knowledgeable for AI technologies.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Managerial capability

19. We have clear goals and objectives to adopt AI technologies.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

20. We have great project management team.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

21. The inter-department cooperation is very important to adopt AI technologies.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

22. The inter-department communication is very important to adopt AI technologies.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

23. Formal education and training programs can be developed to include all classes of users ranging from managers to shop floor controllers.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Managerial support

24. Our managers explicitly demonstrate to support the adoption of AI.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

25. Our managers are willing to take risks involved in the adoption of AI.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

26. Our managers have the ability to exploit new technologies before our competitors

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

27. Our managers have the ability to leverage IT new technologies as a strategic core competence

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

28. Our managers have a strong understanding of how AI technology can be used to increase business performance.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Technical capability

29. We have standardized process for IT innovation.

    1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

30. We have the ability to quickly integrate new AI technologies into our existing infrastructure

    1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

31. Our IT strategies supports our business strategies

    1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

32. We have suitable hardware/software to protect the security and privacy of our systems and networks.

    1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Innovation attributes of AI

Compatibility

33. AI application is compatible with our current communication/network environment.

    1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

34. AI application is compatible with our current software environment.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

35. AI application is compatible with our current hardware environment.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

36. AI application is compatible with our infrastructure

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

37. AI application is compatible with computerized data resources

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Relative advantage

38. AI application can increase revenues and profitability.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

39. AI application can get higher employee productivity.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

40. AI application can improve customer service.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

41. AI application can better utilize IT resources.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

42. AI application can promote flexibility and integration.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Relative risk/complexity

43. Adopting AI innovation lacks application maturity.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

44. There has been a high cost for AI application and migration.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

45. Adopting AI innovation is time consuming.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

46. Inappropriate staffing and personnel shortfalls are a big issue for adopting AI.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

AI adoption

47. A timely AI technical implementation and application migration plan has been developed

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

48. The plan has already been endorsed by managers.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

49. A financial budget and a migration schedule have been approved.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

50. Our customers highly accept new products and services using AI innovations.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

51. We get improvement in the competitive position after adopting AI innovation.

1) Strongly disagree 2) Disagree 3) Somewhat disagree 4) Neutral 5) Somewhat agree 6) Agree 7) Strongly agree

Other questions:

Background Information

52. If you're anticipating that your company will adopt AI in the future. How do you think it will happen? At what stage of AI adoption is your organization currently engaged?

    1)Not considering 2) More than 5 years 3) Between 2 and 5 years 4) between 1 and 2 years 5) Less than 1 year 6) Have already adopted service, infrastructure or platforms of AI.

53. Which of the following AI applications do you think your company should adopt first?

    1)Chatbot 2) Voice Assistant 3) Intelligent Network Management 4) Build Artificial Intelligence Platform 5) Others

54. Current position

    1)General manager 2) Senior manager 3) Middle manager 4) IT engineer 5) Others

55. Number of employees

    1)Less than 500 2) 500-999 3) 1000-1400 4) 1500-1999 5) 2000-2499 6) Over 2500

56. Annual sales ($) for most recent year

    1)Less than 100 million 2) 100-499 million 3) 500-1 billion 4) over 1 billion

57. Enterprise affiliation

    1)Headquarter 2) Provincial level 3) Municipal level 4) County level

58. Group of companies

    1)Unicom 2) Telecom 3) Mobile 4) Tower 5) Others ----

59. Age

1)21-30 2) 31-40 3)41-50 4) 51-60 5)>60

60. Level of education

1)High school 2) Associate 3) Bachelor 4) Master's level 5) Doctoral level

Appendix C. Survey (Chinese version)

关于影响人工智能实施的关键成功因素的调查问卷

此问卷是调查关于影响企业实施人工智能的关键成功因素，适用于实施或计划实施人工智能技术和应用的企业。此调查主要作为研究使用，您在本研究中提供的任何信息都将会妥善保存，不会泄露 。完成此调查大约需要 20 分钟，感谢你花费宝贵时间完成这份重要的问卷。

背景介绍

人工智能是研究、开发用于模拟、延伸和扩展人的智能的理论、方法、技术及应用系统的一门新的技术科学。人工智能主要包含以下不同的领域：

1. 机器视觉。机器视觉是指使用摄像机和计算机来取代人眼对物体的识别，跟踪和测量，使计算机的处理更适合人眼的观察。机器视觉技术可广泛应用于视频监控，自动驾驶，车辆/人脸识别，医疗影像分析及工业自动化系统等领域。

2. 专家系统。专家系统是一个计算机系统，包括知识库，推理引擎和用户界面。 它通常用于辅助决策支持的过程和帮助解决问题。

3. 自然语言的理解。自然语言的理解包括自然语言处理（NLP），语音识别和语音合成。自然语言处理可实现计算机理解自然语言文本、思想和意图，并使计算机用自然语言文本表达思想或意图。自然语言处理可用于机器翻译、字幕生成、文本语义对比等。语音识别和合成技术其可实现人机语言交互、语音控制、声纹识别等功能，可广泛应用于智能音箱、语音助手等领域。

4. 机器学习。机器学习是实现人工智能的一种方法，可以提供算法，API（应用程序编程接口），数据以及计算能力，以便将设计的模型训练和部署到应用程序，进程和其他计算机中。 它主要用于指纹识别，人脸检测和物体检测。

5. 深度学习。深度学习也称为深度神经网络，是一种特殊类型的机器学习。它使计算机能够从经验中学习，并基于概念层次来理解事物。 深度学习擅长识别图像、声音、视频、文本等非结构化数据，几乎可用于当下所有热门的人工智能应用领域。

目前人工智能技术在电信行业的主要应用：

1. 智能客服，指以人机交互方式面向用户提供 7×24 小时的智能应答服务。例如移动研发的智能自服务机器人“移娃” ，单月与客户交互量已达 2 亿多次。同时，通过语音语义分析等人工智能技术，质检部门能及时发觉敏感投诉关键词，及时处理客户投诉和不满；还可结合情感分析技术对客服满意度进行预判，提升客服质量和优化客户体验。

2.智能语音助手。语音助手可为客户提供个性化服务。客户通过语音和文本来控制语音助理来导航电视，拨打电话或访问其他服务。例如法国移动电信公司 Orange 发布了一款名为 Djingo 的人工智能虚拟助手，客户可以通过语音或文本控制 Djingo 来操控电视、打电话、发信息以及提问题。

3.智能网络运营监控和管理。人工智能技术的应用使网络逐渐智能化，可对网络和业务实现智能控制，如网络智能运维及智能调优，通过机器学习快速拦截恶意行为、预防攻击，维护网络安全等。

4.构建人工智能关键技术平台和能力。人工智能平台面向智慧连接、智慧决策、智慧服务等各种场景，更好地支撑和服务人工智能产业以及各行业的智能化转型。例如中国移动的九天平台。

总之，人工智能是引领未来的战略性技术，是全球新一轮信息化发展和产业竞争的核心驱动力。人工智能在通信行业的应用和发展正处于起步阶段。以下问卷中的人工智能包括上述各项研究领域及行业应用。如果您对人工智能不太熟悉，为便于理解和思考，您可以设想您所在公司准备实施人工智能的某项应用，例如智能客服机器人，智能网络自我诊断及调优，语音助手，以及客户数据的挖掘与分析等。

请以数字 1-7 的等级对以下叙述表明您的意见，1 代表非常不同意，4 代表没意见，7 代表非常同意。所有的叙述没有正确或错误的答案，您只需表明您的看法即可。

政府

1. 政府政策的规范和稳定性有利于企业经营和创新。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

2.政府能为我们发展人工智能业务提供资金支持。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

3.政府能为我们发展人工智能业务提供相关的信息。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

4. 我们需要与政府建立良好的关系以更好地发展人工智能业务。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

5. 政府的支持和帮助对我们的经营和创新非常重要。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

市场潜力

6. 我们所在的行业将有更多的人工智能技术用于业务开发和应用。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

7. 人工智能在我们行业有非常广泛的应用前景。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

8. 只有人工智能这类创新技术才能帮助我们公司提供更完美的产品和服务，以满足消费者日益增长的个性化需求。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

9. 人工智能可以帮助我们公司获取市场竞争力。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

竞争压力

10. 我们所在行业的新运营流程和新产品或服务的创新速度加剧。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

11. 我们所在行业转向利用人工智能技术进行创新会给我们公司带来压力。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

12. 我们行业竞争非常激烈。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

13. 我们的产品和服务质量竞争非常激烈。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

供应商/合作伙伴合作关系

14. 我们从供应商/合作伙伴那里获得帮助没有任何困难。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

15. 我们的供应商/合作伙伴非常值得信赖。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

16. 我们的供应商/合作伙伴的决策对我们很有利。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

17. 我们和供应商/合作伙伴的关系非常密切。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

18. 我们的供应商/合作伙伴对人工智能技术非常了解。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

管理能力

19. 我们对采用人工智能技术有非常明确的目标。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

20.我们有非常优秀的项目管理团队。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

21.部门间的合作对采用人工智能技术非常重要。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

22.部门间的有效沟通对采用人工智能技术非常重要。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

23.我们可以对创新业务制定正式的教育和培训计划，涵盖从最高管理层到基层员工的的所有类别的培训对象。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

管理层支持

24.我们的管理层明确表示支持采用人工智能新技术进行创新经营。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

25.我们的管理层人员愿意承担采用人工智能技术的风险。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

26.我们的管理层有能力抢在竞争对手之前拓展新技术/新业务。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

27.我们的管理层有能力利用 IT 新技术例如人工智能作为战略核心竞争力。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

28.我们的管理层对如何利用人工智能技术提高业务绩效有着深刻的理解。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

技术能力

29.我们有标准化的 IT 创新流程。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

30. 我们有能力将新的人工智能技术快速集成到现有的基础设施中。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

31. 我们的技术发展战略支持我们的业务发展战略。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

32. 我们有相应的硬件/软件来保护我们系统和网络的安全。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

AI 技术的兼容性

33. 人工智能应用程序与我们当前的通信/网络环境兼容。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

34. 人工智能应用程序与我们当前的硬件环境兼容。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

35. 人工智能应用程序与我们当前的软件环境兼容。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

36.人工智能应用程序与我们当前的基础架构兼容。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

37.人工智能应用程序与我们当前的数据资源兼容。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

AI 技术的优势

38.采用人工智能技术可以增加我们的盈利能力。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

39.人工智能应用程序可以提高工作效率。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

40.人工智能应用程序可以改善客户服务。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

41. 人工智能应用程序可以更好地利用 IT 资源。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

42. 人工智能应用程序可以提高业务应用的灵活性和集成性。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

AI 技术的复杂性

43. 人工智能技术缺乏应用成熟度。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

44. 人工智能应用和迁移的成本很高。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

45. 应用人工智能创新业务非常耗时。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

46. 人员配置不当和专业技术人员短缺是采用人工智能的一个大问题。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

人工智能应用

47.我们已经制定了人工智能技术实施和应用程序迁移计划。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

48.我们制定的计划已经得到公司管理层的认可。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

49.关于计划的财务预算和实施时间表已获批准。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

50.我们的客户高度接受使用人工智能创新的新产品和服务。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

51.采用人工智能技术开展创新业务后，我们的竞争地位得到了提升。

1)非常不同意 2)完全不同意 3)有点不同意 4)没意见 5)有点同意 6)完全同意 7)非常同意

其他问题

52.您预计您所在的公司将来会采用人工智能新技术吗？

1）没考虑过　2）5 年后　3）2-5 年内　4）1-2 年内　5）一年之内 6）已经开始应用了

53.您认为公司最应该首先采用以下哪种人工智能应用

1）聊天机器人 2）语音助手 3）智能网络管理 4）搭建人工智能平台 5）其他-----

54.您目前的职位

1)公司总经理　2）高层管理人员 3）中层管理人员 4）技术工程师　5）其他-----

55.公司员工数量（人）

1）小于 500　2）500-999　3）1000-1499　4）1500-1999　5）2000-2499　6）大于 2500

56.公司最近一年年收入

1)小于 500 万 2）500-999 万　3）1000 万-4999 万 4）5000 万-1 亿 5）1 亿-10 亿 6）大于 10 亿

57.公司从属关系

1)总部/集团公司　2）省级分公司 3）市级分公司 4）县级分公司

58.公司所属集团

1）联通 2）电信　3）移动　4）铁塔　5）其他----

59.您的年龄

1)21-30　2) 31-40　3) 41-50　4) 51-60　5) >60

60.您的受教育程度

高中 2) 大专 3) 本科 4) 研究生 5) 博士及以上

VITA

Hong Chen

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Education

Ph. D.	Information Technology *(current status: ABD. GPA:3.8/4.0)*	2019 (*August)*	Old Dominion University Norfolk, VA
M. A.	Electronics and Communication Engineering	2007	Tianjin University Tianjin, China
B. A.	Computer information management	2001	Hebei University Baoding, China

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Journal Publications

Liang, X., **Chen, H**., (2018) "The application of CPS in library management: a survey", *Library Hi Tech*, https://doi.org/10.1108/LHT-11-2017-0234

Chen, H. (2017). Applications of Cyber-Physical System: A Literature Review. *Journal of Industrial Integration and Management*, *2*(03), 1750012.

Chen, H. (2017). Theoretical Foundations for Cyber-Physical Systems: A Literature Review. *Journal of Industrial Integration and Management*, *2*(03), 1750013.

Chen, Y., **Chen, H**., Gorkhali, A., Lu, Y., Ma, Y., & Li, L. (2016). Big data analytics and big data science: a survey. *Journal of Management Analytics*, *3*(1), 1-42.

Chen, Y., Dong, F., & **Chen, H**. (2016). Business Process and Information Security: A Cross-Listing Perspective. *Journal of Industrial Integration and Management*, *1*(02), 1650009.

Proceedings

Chen, H., & Chen, Y. (2017). Does Legal Protection from Host-countries Mitigates Information Security Risk in Multinational Enterprise Subsidiaries. *The Americas Conference on Information Systems* (*AMCIS) 2017, Boston, MA.*

Chen, H., & Chen, Y. (2017). Does the Impact of Sentiment on Firm Financial Performance Transmit in Supply Chain? *Decision Sciences Institute (DSI) 2017, Washington, DC.*

Chen, H., & Chen, Y. (2017). Supplier Selection in the Global Market: A Buyer Animosity Perspective. *Decision Sciences Institute (DSI) 2017, Washington, DC.*

Chen, Y., **Chen, H**., & Xu, L. (2016, August). Social Media and eBusiness: Cultural Impacts on the Influence Process in Consumer Communities. In *IOP Conference Series: Materials Science and Engineering* (Vol. 142, No. 1, p. 012134). IOP Publishing.

Chen, Y., Dong, F., & **Chen, H**. (2016). Can cross-listing mitigate the impact of an information security breach announcement on a firm's values? *The Americas Conference on Information Systems* (*AMCIS) 2016, San Diego, CA.*

Li, L., Xu, L., He, W., Chen, Y., & **Chen, H**. (2016, December). Cyber Security Awareness and Its Impact on Employee's Behavior. In *International Conference on Research and Practical Issues of Enterprise Information Systems* (pp. 103-111). Springer, Cham.